# SYNOPSIS

# Investigation on Correlation between Rebound Index and Compressive Strength of Concrete


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## ABSTRACT

Non-destructive testing (NDT) is vital in finding the surface hardness of concrete members. The B-Proceq curve can calculate the concrete strength by providing statistical correlations between the destructive and the non-destructive strength. The regression curve based on the laboratory test may be valid within their implementation boundaries. It is not feasible to extend the validity of these curves to the in-situ test. Factors influencing such curves include the w/c ratio, carbonation effect, exposure to fire, compaction, curing condition, type of cement used in concrete, etc. More than 65 years of research data with the Schmidt rebound hammer is used for evaluation. Various factors significantly affect the rebound index, so their consideration while conducting a rebound test is necessary. The significant deviation of curves raised a crucial question of whether the rebound hammer is effective or not in estimating concrete strength.

From an experimental study, it is found that the reduction of the compressive strength of concrete is between 6 to 41 per cent due to insufficient compaction alone when tested using a destructive method. The rebound hardness test cannot predict compressive strength due to inadequate curing. The study revealed that in case of M30 and M40 grades of concrete, the percentage reduction of average rebound index is almost higher than the average compressive strength at a temperature ranging from 200°C to 800°C. The strength (rebound hardness) measured is either under or overestimated if no attention has been given to different influencing factors.

The reliability of result significantly affects use of the Coefficient of Variation (within the test variation), which reflects the variability of the concrete properties rather than the standard deviation. For the estimation of reliability and precision, comprehensive statistical analysis (within test variation) is conducted on 534 test samples using a rebound hammer. Different standards, like BIS, EN, ACI, and ASTM, are used in this study to compare the test results. Empirical research revealed that there are contradictions in literature as well as the standards used in many countries. The present study focuses on detailed investigations of uncertainty measurements of the surface hardness test by statistical parameters. The unbiased estimate of the variability parameters from the published results has been verified concerning the European standard. Based on the results, the authors are willing to propose amendments to the Indian code graciously in compliance with the variability of the rebound hammer.

Assessing structural concrete strength by the core test of the in-situ structures is expensive and technically challenging. The reliability of this calibration is a crucial task that leads to the selection of a minimal number of cores. The present study aims to identify and optimize the on-site reliability model. The data of core samples tested with non-destructive methods, i.e. Rebound Hammer and Ultrasonic Pulse Velocity tests, were collected from the Construction Diagnostic Center, Pune, which tested 30 existing RC structures constructed between 1975 to 2005. Statistical analysis allows the quantitative evaluation of part of the cores used for calibration and NDT (Single and Combined Method) methods. The findings are based on a broad dataset to enhance the relevance of prediction models, which are very useful in estimating the concrete strength of existing structures.



***Keywords*:** Compressive strength, Properties of concrete, Rebound index, Regression analysis, Repeatability, Statistical analysis, Prediction model, Non-destructive methods, On-site evaluation, Cores pulse velocity, Ultrasonic Pulse Velocity (UPV), Rebound hammer(RH), ANFIS, Numerical modeling.

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## ABBREVIATION NOTATION AND NOMENCLATURE

| | |
|---|---|
| *SM* | *Single method* |
| *CM* | *Combined method* |
| *L* | *Laboratory results,* |
| *C* | *Core results, B: Blend mix,* |
| *L-$B_1$- $B_3$:* | *Cement grade,* |
| *L-$B_4$- $B_7$:* | *Water to cement ratio (0.35 to 0.50),* |
| *L-$B_8$-* | *Curing and compaction (Air, water and No, Manual, Vibratory),* |
| *L-$B_9$- $B_{11}$:* | *Elevated temperature (200 to 800$^oC$),* |
| *C-$B_{12}$- $B_{17}$:* | *Core results,* |
| *$f_{cm}$:* | *Compressive strength,* |
| *CV:* | *Coefficient of Variation* |
| *$CG_1$, $CG_2$, $CG_3$* | *Cement grade* |
| *$M_{15}$, $M_{20}$ and $M_{25}$* | *Mixes* |
| *$R^2$ -* | *coefficient of determination,* |
| *NC-* | *Number of cores,* |
| *NT-* | *Total number of test locations for NDT measurements* |
| *a, b, c, d* | *Coefficient* |
| *COV* | *Concrete strength variability (in terms of coefficient of variation)* |
| *DT* | *Destructive test method (cores)* |
| *fcm* | *Compressive strength* |
| *fcest* | *Estimated Compressive strength* |
| *NDT* | *Nondestructive test* |
| *RMSE* | *Root mean square error* |
| *SD* | *Standard Deviation* |
| *Kb, Ka* | *Hammer mass kinetic energies just before and immediately after impact* |
| *NVC* | *Normally vibrated concrete* |
| *SCC* | *Self-compacting concrete* |
| *R* | *Rebound hardness* |
| *CT-I, CT-II, CT-III* | *Types of cement* |
| *$R_{max}$, $R_{min}$* | *Range of rebound number* |
| *$S_R$* | *Standard deviation of rebound index* |
| *$CV_R$* | *Coefficient of variation of rebound index* |
| *$R_r$* | *Range of rebound index* |
| *øR* | *Studentized range* |
| *$P_{fc}$* | *Normality range Compressive strength* |
| *$P_R$* | *Normality range Rebound number* |
| *V* | *Volume* |
| *Rm* | *Mean rebound number* |
| *UPV* | *Ultrasonic pulse velocity* |

# CHAPTER 1
# INTRODUCTION

## 1.1. RESEARCH PROBLEM

The regression curve based on the laboratory test may be valid within their implementation boundaries. It is not feasible to extend the validity of these curves to the in-situ test. The significant deviation of curves raised a crucial question of whether the rebound hammer is effective or not in estimating concrete strength. The strength (rebound hardness) measured is either under or overestimated if no attention has been given to different influencing factors. For the estimation of reliability and precision, comprehensive statistical analysis (within test variation) is conducted on 534 test samples using a rebound hammer.
The present study focuses on detailed investigations of uncertainty measurements of the surface hardness test by statistical parameters. The data of core samples tested with non-destructive methods, i.e. Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV) tests, were collected from the Construction Diagnostic Center, Pune, which has tested 30 existing RC structures constructed between 1975 to 2005. Statistical analysis allows the quantitative evaluation of part of the cores used for calibration and NDT (Single and Combined Method) methods. The findings are based on a broad dataset to enhance the relevance of prediction models, which are very useful in estimating the concrete strength of existing structures. Ali Benyahia et al. (2017) [1] pointed out that the technological challenge had to test the model identification approach's real dataset at the prediction stage.

For accurate estimation of carbonation depth, several analytical and empirical investigations have been performed (Chang and Chen 2006 [2], Monteiro et al. 2012 [3]). The current work is developing a reduction coefficient equation that accounts for errors in the rebound index produced by carbonated concrete, therefore removing one of the rebound hammer test's primary disadvantages. Unlike earlier research in recent decades, the proposed equation provides a reduction coefficient of a rebound index based on the carbonated depth rather than the structural age of concrete. This reduction coefficient is calculated using a modelling approach and compared to the experimental outcome published in the literature (Breccolotti (2013) [4] and Kim (2009) [5]). The level of carbonation depth is related to factors such as age (time), core height and diameter ratio, core equivalent cube strength and rebound index. These factors were considered while predicting the carbonation depth using the ANN/ANFIS system. This system is based on the result dataset obtained from field investigation, and the accuracy of the ANFIS system is compared with measurement results obtained from the destructive and non-destructive applications.

## 1.2. RESEARCH GAP

1. Empirical curves derived by researchers are widely scattered, emphasizing the influencing factors' effects.
2. Observer adds an inherent observational error to the readings of the rebound index in favour of the even numbers due to the Scale Device.
3. The specific curve for the hardness test is not arbitrarily set to the minimum level.

4. No calibration curves considering various influencing factors are available.
5. The minimal number of cores required for reliability estimates varies from researcher to researcher.
6. Assessment needs more attention to the test variability of existing and proposed reliability models.
7. Concerning carbonation depth, there is no provision for a reduction coefficient in the rebound index.

### 1.3. RESEARCH OBJECTIVES

1. To investigate the mechanical and physical properties of concrete with rebound hammer considering various factors such as water to cement ratio, compaction deficiency, curing condition, elevated temperature, carbonation effect and types of cement.
2. To find the correlation between the rebound index and concrete's destructive strength.
3. To carry unbiased estimate of the variability parameters of the experimental outcomes as perthe European standard.
4. To conduct a comprehensive statistical analysis (within test variation) of the repeatability ofthe rebound hammer results as per various standards for reliability estimation.
5. To study the effect of carbonation depth on rebound index obtained from existing structuresusing ANFIS and FEM analysis.
6. To suggest reduction coefficient with respect to factors under consideration or affecting performance of RH.

### 1.4. COMMENTS BY LAST RRC

| **Recommendations** | **Remark / Implementation** |
|---|---|
| a) ANN should be used for getting the combined effect. | a) ANN tool is employed for prediction of data and results (Page no. 27) |
| b) Essential details of FEM analysis [2D or 3D, Element type, Boundary conditions, Constitutive relationship, material properties] should be elaborated. | b) Details are added in the report and the presentation both. (ABAQUS FEM analysis- Non and Fully carbonated properties (Concrete Damaged Plasticity constitutive model- CDP) (Table 3.7), Load and boundary conditions for carbonated concrete (Table 3.8), apply to C3D8R type of Element with explicit Reduced integration scheme (Fig. 3.7) to describe the inelastic behavior of the carbonated concrete. |

# CHAPTER 2
# LITERTURE REVIEW

## 2.1. REBOUND NUMBER-STRENGTH RELATIONSHIPS

Schmidt hammer provides the relationship in the form of equations and graphs between measured values of rebound index and compressive strength of concrete specimens. A comprehensive interpretation should cover all factors of concrete structure, including grade variation, cement type, compaction, carbonation, cured condition, exposed temperature, and moisture content. Many researchers (Table 2.1) investigated how the rebound index correlates with destructive compressive strength.

Table 2.1. Statistical relationships between compressive strength of concrete (fcm) and rebound number (R) [59]

| Authors | Influencing factors (Boundary conditions) | Equations | Regr. Appr. |
|---|---|---|---|
| Proceq (2008) [6] | Original Schmidt hammer | $f_{cm}$= 0. 0117.$R^2$ + 0.8973.R- 13.213 | Poly. |
| Kheder (1999) [7] | W/C ratio, Curing age and concrete mix | $f_{cm}$= 0.403.$R^{1.2083}$ | Power |
| Balkrishna et al. (2017)[8] | | $f_{cm}$=2.6723$e^{0.0479R}$ | Power |
| Szilágyi et al. (2015) [9] | | $f_{cm}$ = 11.04x$10^{-2}$.$R^{1.739}$ | Power |
| Qasrawi (2000) [10] | W/C Ratio, Compaction, Mould material effect (0.50, vibration, cube 150 mm) | $f_{cm}$=1.353.R-17.393 | Linear |
| Hobbs, Kebir (2006) [11] | W/C Ratio, Compaction | $f_{cm}$= 2.1683. R- 27.747 | Linear |
| Pascale et al. (2003) [12] | Types of hammer used | $f_{cm}$= 0.0002392.$R^{3.299}$ | Power |
| Brozovsky and Bodnarova (2016) [13] | (N type hammer) | $f_{cm}$= 0.0107$R^2$ + 0.9073R - 12.935 | Poly. |
| | (CSN EN 13791) | $f_{cm}$= 1.73R- 34.5 | Linear |
| Brozovsky (2014) [14] | Types of hammer and aggregate | | |
| | (L type, Basalt aggregate) | $f_{cm}$= 0.0076 $R^{2.4229}$ | Power |
| Kim et al. (2009) [5] | Carbonation effect in days | - | |
| | (360 days) | $f_{cm}$ = 1.72R–37 | Linear |
| Yang et al. (2018) [15] | Carbonation depth (dm) is 6mm for 28 days and w/c ratio- 0.58) | $f_{cm}$= 0.05853.$R^{1.814985}$ . $10^{-0.0475dm}$ | Power |
| Monteiro and Goncalves (2009) [16] | Influence of Core specimen | $f_{cm}$ = 1.14R–21.8 | Linear |
| Di Leo et al. (1984) [17] | | $f_{cm}$= 0.00883. $R^{2.27}$ | Power |
| Antonio et al. (2013) [18] | | $f_{cm}$= 0.0103.$R^2$ + 0.3586.R + 8.2986 | Poly. |
| Goncalves (1995) [19] | | $f_{cm}$= 1.73.R-34.3 | Linear |
| EN 13791 (2007) [20] | | $f_{cm}$= 1.73.R-34.5 | Linear |
| Aydin and Saribiyik (2010) [21] | Influence of Curing age | | |
| | 28 days | $f_{cm}$ = 11.612R–52.033 | Linear |
| | 90 days | $f_{cm}$ = 11.674R–238.31 | Linear |
| Zabihi (2012) [22] | (Cooled in air - 28 days) | $f_{cm}$ = 0.0953.R + 31.887 | Linear |
| | (Cooled in water - 28 days) | $f_{cm}$ = 0.3187.R + 21.055 | Linear |
| | Influence of grade of concrete | | |

| | | | |
|---|---|---|---|
| Duna et al. (2014) [23] | (M 20) | $f_{cm}$= -0.011$R^2$ + 1.282R - 2.844 | Poly. |
| | (M 30) | $f_{cm}$= -0.002$R^2$ + 0.829R + 2.422 | Poly. |
| | (M 35) | $f_{cm}$= 0.001$R^2$ + 0.519R + 7.343 | Poly. |
| Mikulic et al. (1992) [24] | Grade of concrete (M20 to M35) | $f_{cm}$ = 2.50.R-18.4 | Power |
| Nash't et al. (2005) [25] | Cement type, Grade | $f_{cm}$= 0.788.$R^{1.03}$ | Power |
| Brozovsky and Bodnarova (2016) [13] | Effect of elevated temperature | | |
| | (Before heat load $0^0$c) | $f_{cm}$ =0.0425. $R^2$ + 1.4965. R + 25.294 | Poly. |
| | (After heat load $200^0$c to $800^0$c) | $f_{cm}$= 1.55.$e^{0.0648R}$ | Power |
| Abdulkadir et al. (2017) [26] | Effect of exposed to fire | | |
| | (All mixes cooled in air) | $f_{cm}$ = 1.773R–27.58 | Linear |
| | (All mixes cooled in water) | $f_{cm}$ = 1.75R–26.357 | Linear |

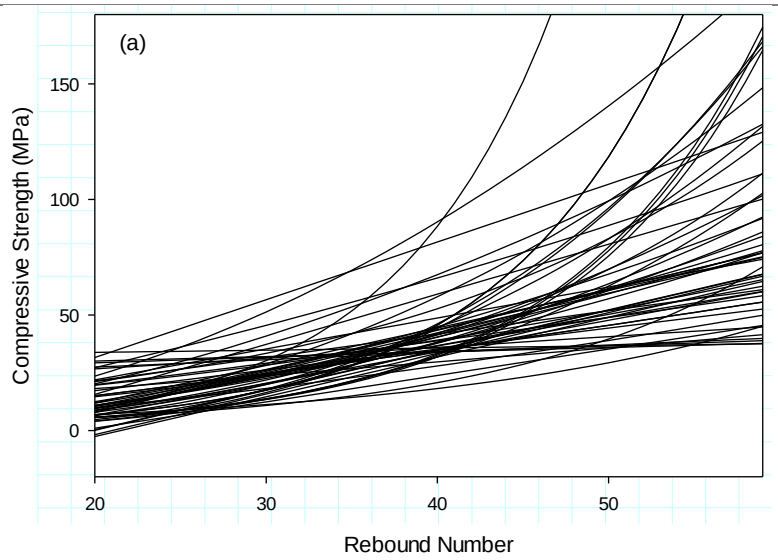



Fig. 2.1 Empirical curves derived by different researchers considering influencing factors

More than 65 years of research data with the Schmidt rebound hammer is used for evaluation. The large deviation of curves as shown in Fig. 2.1 raised a crucial question of whether the rebound hammer is effective or not in estimating the concrete strength.

## 2.2. EFFECT OF INFLUENCINF FACTORS ON REBOUND INDEX

IAEA (2002) [27] stated that the variation in the rebound results would exceed 50% due to the application of different types and cement content. Bungey (2006) [28] reported in their studies that the strength of concrete increases with an increasing degree of compaction. When fresh concrete is poured into the formwork, air voids can consume 5 to 20% of the total volume. Szilagyi (2013) [29] reported that a comparative analysis of the strength of the specimens cured underwater and only in air conditions will show the influence of curing conditions on concrete strength. Yang (2018) [15] reported that both the rebound value and the compressive strength of high-performance concrete had increased with a decrease in the W/C ratio.

## 2.3. REPETABILITY OF REBOUND HARDNESS

Alwash (2015) [30] indicated that modestly reducing the variability of the rebound values found in the test contributes toward a more accurate evaluation. ACI committee (2003) [31] suggested that the reliability study primarily focuses on using the within-test evaluation

(Coefficient of Variation- dispersion parameter) to understand the uncertainty of different materials' properties instead of the standard deviation over the strength range.

ACI committee (2003) [31] suggested the determination of the compressive strength of the concrete by the surface hardness test method should take into account several levels of uncertainties: a. uncertainty associated with the results of the surface hardness test, b. uncertainty related to the surface hardness and strong correlation, c. within test variability of the concrete strength. According to the committee of the (RILEM TC249-ISC (2019) [32]), the European standard is dedicated to assessing strengths in concrete buildings, with a particular emphasis on evaluating concrete strengths.

## 2.4. RELIABILITY OF PREDICTION MODEL

The statistical characteristics of the fitted and predicted model dataset are inefficient, and the resulting reliability of the model is a questionable issue during the prediction phase. However, the reliability of the estimated strengths could be less than the uncertainty in the fitted model. The difference between fitted and prediction errors in the model generally evolves due to the generalization of the model approach.

Benyahia et al. (2017) [1] pointed out that the technological challenge had to test the model identification approach's real dataset at the prediction stage. Alwash et al. (2017) [33], Pucinotti (2015) [34], and Breysse (2012) [35] reported that in some instances, only one NDT method leads to unreliable strength estimates, hence it is always better to combine NDT methods (RH and UPV) to ensure higher reliability of the estimated concrete strength. Uncontrolled factors affect the reliability of estimated NDT based on: a. scatter and b. several test results were used to develop the prediction model.

Fiore (2013) [36] pointed out that NDT test results correlated with core strengths provide a better option for structural strength evaluation. An empirical relation must be formed between the NDT results and the strengths of cores taken from the same locations. European standard EN13791 [20] suggested at least 18 sets, and the ACI 228.1R report indicated that at least 6 to 9 sets are needed to develop the prediction model. Alwash et al. (2017) [33] suggested that actual practices typically use only 3 or 4 cores. The Ministry of Railways-India [37] said that the probable accuracy of estimating concrete strength in a structure using the rebound hammer is ±25%.

According to the European standard EN 13791 [20], ten cores and companion results are required to develop the prediction model. According to the ACI 228.1R-03, at least six pairs of cores are needed for the regression approach. RILEM NDT-7 [38] recommended a process to develop iso-strength curves for concrete using materials and mixtures from different countries. The curves are generated and based on combined RH and UPV testing. A correction factor can be applied to the iso-strength curves if the mixture is known. The correction factor should be estimated using cores extracted from the structure under investigation if it is unknown.

## 2.5. ANFIS/FEM APPRAOCH

Different researchers show their implementation in ANFIS and ANN models for estimation of carbonation depth, which is shown briefly in Table 2.2.

Table 2.2: Model used for estimation of carbonation depth by different researchers

| Authors | Model used | Application (Estimation of carbonation depth) |
|---|---|---|
| Cho et al. (2016) [39] | ANFIS (Sugeno fuzzy inference system) | Input parameters: surface chloride ion concentration, chloride ion diffusion coefficient, concrete compressive strength, and crack width<br>Dataset: 8 Buildings<br>System: Optimized ANFIS algorithm<br>Output: The suggested model accurately represented the combined effects of all input variables; determining carbonation depth is based on the combined deterioration; and the method is especially useful in a building where investigations are carried out on a regular basis. |
| Malami et al. (2021) [40] | ANFIS (Hybrid Neuro-fuzzy model), Extreme Learning Machine (ELM), Support Vector Machine (SVM), Multilinear Regression (MLR) Model | Input parameters: age, compressive strength, current density, and carbonation constant<br>Dataset: Building structures in North Cyprus have a higher rate of carbonation than is expected over their lifetime.<br>Output: In all the testing and training stages, AI models (ANFIS, ELM, and SVM) outperformed the linear model (MLR) with NSE-values more than 0.97, demonstrating the ability of non-linear models (ANFIS, ELM, and SVM) in Cd prediction. |
| Dede et al. (2019) [41] | Artificial neural network (ANN) | Input parameters: self-consolidating concrete exposed to different sodium sulphate.<br>Dataset: concrete at 28 days<br>Output: predicting the compressive strength using an AI-based technique (neuro-fuzzy), investigation of carbonation issues. |
| A. Malik (2021) [42] | ANFIS | Application: data intelligent algorithm, controlling the experimental time series associated with the problem, black-box model. |
| Lu and Liu (2009) [43] | Two ANN model- Radial basis function neural network (RBFNN) and Backpropagation neural network (BPNN) | Input parameters: accelerated carbonation, stress level in carbonation process.<br>Dataset: pre-stressed concrete<br>Output: two ANN models predict carbonation depth with high accuracy. |
| Taffese et al. (2015) [44] | Carbonation prediction model (CaPrM) | Input: monitoring the process of carbonation by integrating 4 learning methods and 25 input variables.<br>Dataset: 23 various types of concrete mix.<br>Output: integrating machine learning methods improves |

| | | |
|---|---|---|
| | | carbonation prediction with high accuracy. |
| Akpinar and Uwanuakwa (2016) [45] | Artificial neural network (ANN) | Input: 18 input variables<br>Dataset: carbonation depth in reinforced concrete (NDT result)<br>Output: ANN model predict the carbonation progress with higher accuracy. |
| Akpinar and Uwanuakwa (2020) [46] | Artificial neural network (ANN) model scaled conjugate gradient (SCG) | Input: 18 parameters using an alternative scaled conjugate gradient (SCG).<br>Output: Using an ANN architecture to improve the accuracy of carbonation modelling and prediction, parametric analysis results agreed with traditional practise, allowing researchers to investigate the scope of the carbonation problem in concrete. |
| Paul et al. (2018) [47] | Automated neural network search (ANS) | Input parametres: concrete composition, weathering, exposure condition, and time of depth of carbonation in concrete.<br>Dataset: various concrete mixes<br>Output: carbonation depth estimated by adopting a composition of the concrete mixture. Validation of experimental results through ANS model with higher accuracy. |
| Felix et al. (2019) [48] | Artificial neural network (ANN) | Input parameters: CO2 dispersion in concrete, carbonation depth over time.<br>Output: An ANN model is used to assess the long-term viability of engineering projects. CO2 dispersion in concrete is predicted throughout time. |
| Lee, and Suraneni (2020) [49] | Machine learning algorithms, FEM analysis | Input Parameters: experimental results<br>Output: carbonation depth prediction model and deep learning algorithm used for accurate carbonation progress predictor. |
| Alhassan et al. (2020) [50] | Artificial neural network (ANN) | Input parameters: 19 input variables (influencing factors)<br>Dataset: 458 data sets from prestressed concrete structures.<br>Output: The ANN model can maintain a huge database with varied parameters and estimate the transfer length of pre-stressing strands. |
| Houseen and Akpinar (2020) [51] | | Dataset: 149 concrete core samples extracted from 39 buildings (coastal areas of Northern Cyprus)<br>Outcome: Fick's Law was used to forecast carbonation depth for a 50-year-old structure with a 30 mm carbonation depth. Just 41% of inland results met the Euro code (carbonation resistance performance) standard, against 71% of coastal samples. |

# CHAPTER 3
# CONTRIBUTIONS

## 3.1. CONTRIBUTION 1- Correlation between rebound index and destructive strength

The assessment methodology is based on controlled parameters within-test variability and NDT methods (RH). Uncontrolled parameters include the concrete mixture and construction characteristics such as type of cement, type of aggregate, compaction methods, curing conditions, water to cement ratio, maximum temperature, and depth of carbonation as shown in Fig 3.1.

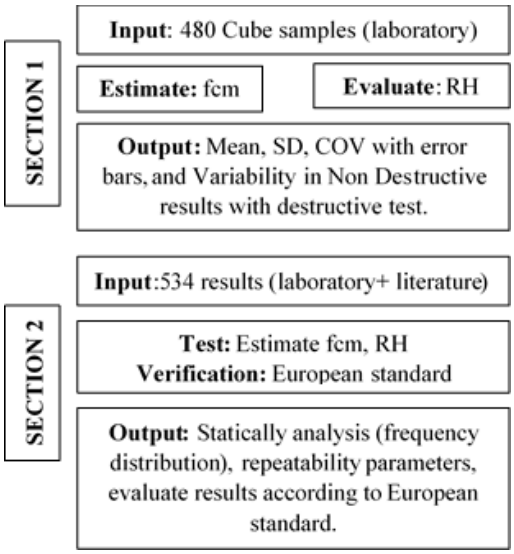

SECTION 1
Input: 480 Cube samples (laboratory)
Estimate: fcm
Evaluate: RH
Output: Mean, SD, COV with error bars, and Variability in Non Destructive results with destructive test.
SECTION 2
Input:534 results (laboratory+ literature)
Test: Estimate fcm, RH
Verification: European standard
Output: Statically analysis (frequency distribution), repeatability parameters, evaluate results according to European standard.

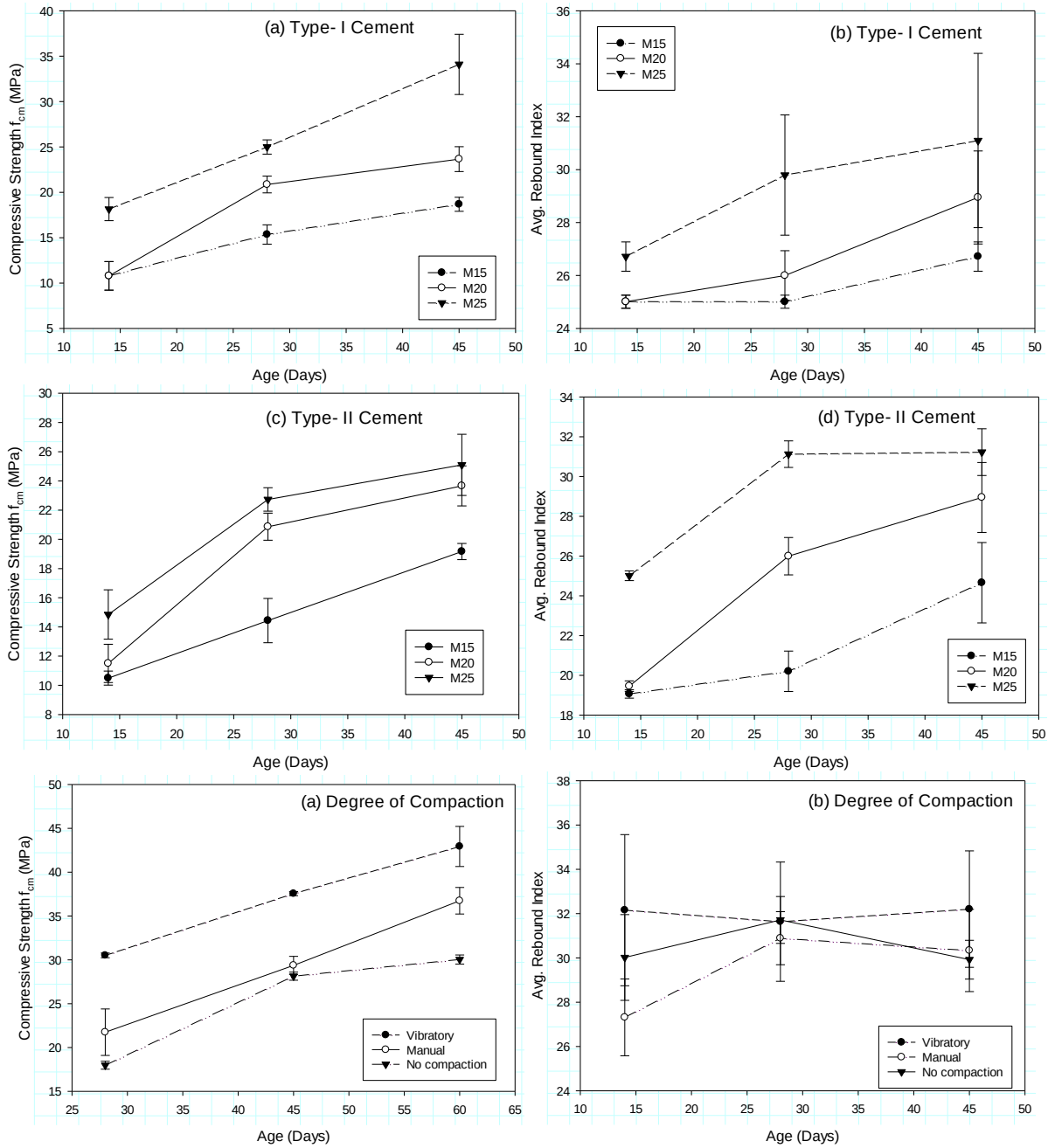
Fig. 3.1 Part- I Assessment methodology based on Laboratory results

The mixes M1 to M5 is related with three types of cement with grades M15 to M40 and different water to cement ratios, these specimens tested after 14, 28 and 45 days by destructive and nondestructive test as shown in Table 3.1.

Table 3.1 Composition of mixes with different influencing factors [61]

| Mix Type | Influencing factors | Grade Mix | Cement Type | Composition/ w/c Ratio | Testing Duration (Days) | No. of cubes |
|---|---|---|---|---|---|---|
| $M_1$ | Cement type (CT I-PPC 53, CT II -PPC 43) | M15, M20, M25 | CT- I, CT- II | 1:1.9:3.9/0.5 1:1.55:2.98/0.5 1:1:2/0.5 | 14, 28, 45 | 54 |
| $M_2$ | Degrees of compaction (No, Manual, Vibratory) | M20 | CT- I | 1:1.5:3/0.5 | 28, 45, 60 | 27 |
| $M_3$ | Curing conditions (Water and air curing) | | | | | 18 |
| $M_4$ | Elevated temperature (200$^o$ to 800$^o$C with Hot and Air-cooled condition) | M20, M30, M40 | | 1:1.49:2.8/0.48 1:0.79:1.48/0.4 1:0.25:0.56/0.36 | 28 | 36 |
| $M_5$ | Water to cement ratio (CT- III - 43 Grade with super-plasticizer Con Plast-500) | M30 | CT- III | 1:1.22:2.45:0.01/0.3, 1:1.58:3.01:0.01/0.36, 1:1.80:3.40:0.01/0.40, 1:2.20:3.90:0.01/0.45 | 7, 28 | 24 |

The variability of trend lines according to the error bars with average compressive strength and average rebound index over different ages is shown in Fig 3.2. In the case of a mix of M15, M20 and M25 with Type-I cement concrete, a similar average rebound index is observed, but there is a uniform increase in the compressive strength. The error bar shows the maximum value for Type-I cement compared to Type-II cement at 28 and 45 days. It may happen due to the fast hardening of Type-II cement concrete at its initial stage than that of Type-I cement concrete. Regarding the w/c ratio, the reduction in average compressive strength with the rebound hammer is almost half that of destructive tests. It implies that the rebound hammer does not give true compressive strength values.



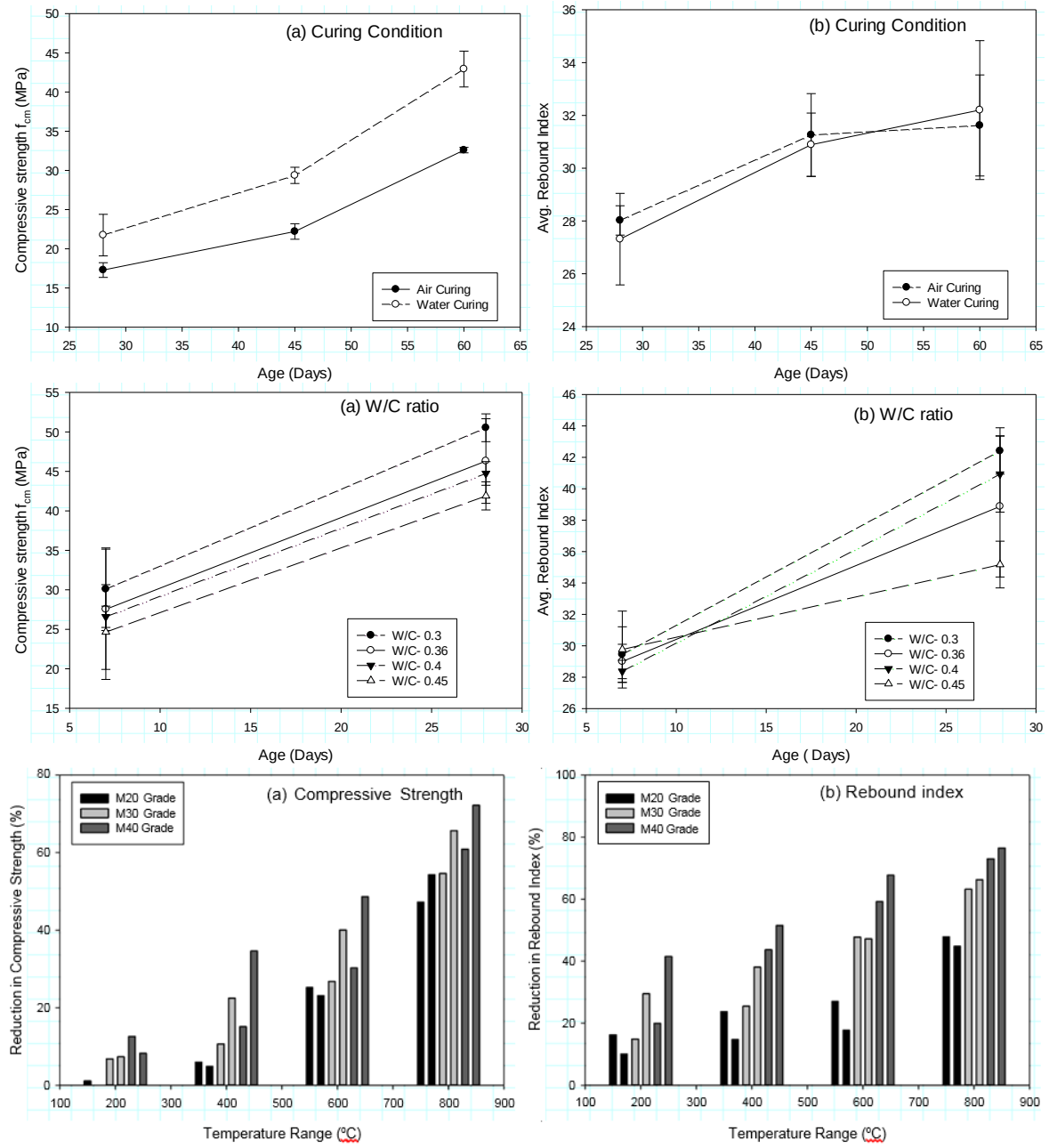



Fig. 3.2 Variation in rebound index and compressive strength for various influencing factors

In the case of compaction deficiency, the reduction in the average rebound index is approximately half that of the decrease in average compressive strength for concrete compacted manually. It indicates that the rebound hammer is ineffective in estimating the strength of concrete compacted by different methods. With varying curing conditions, the average compressive strength varies by 23.56%, whereas the average rebound index varies by just 1.87% for specimens cured with both methods. Therefore, it indicates that the rebound hardness test cannot predict compressive strength influenced by inadequate curing.

Due to the temperature rise, the reduction in compressive strength is higher than the reduction in rebound index. The cube's surface hardness also increased, resulting in a higher rebound index, particularly in higher grades of concrete, i.e. M30 and M40. More significant mass loss occurs as the $CaCO_3$ decomposition starts at higher temperatures ranging from 650°C to 760°C.

### 3.2. CONTRIBUTION 2- Repeatability of rebound index with statistical analysis (European standard)

Extensive data analysis has been done in this paper to investigate the impact of the empirical error on the rebound results. Comprehensive statistical analysis has been prepared from the investigation of considered repeatability parameters suggested by different standards of the rebound surface hardness test, as shown in Table 3.2.

Table 3.2 Repeatability parameters suggested by different standards [60]

| Code | Points considered | Statistical parameter | Points to be claimed |
|---|---|---|---|
| EN13791 (2007) [20] | Establishing a relationship based on at least 18 drilled core strength results, whereas the other researcher proposes a relationship based on at least nine drilled core strength results. | Average rebound index values ($R_{min}$, $R_{max}$) with compressive Strength values ($fc_{min}$, $fc_{max}$) with 10 to 50 percentile. | The basic curve has been set at an artificially low position so that the change is always positive. |
| ACI 228.IR (03) (2003) [31] | Repeatability is referred to as within test variation and reproducibility is referred to as batch-to-batch variation | SD ($S_{max}$- $S_{min}$), COV ($CV_{max}$-$CV_{min}$) over the mean rebound number ($R_{max}$- $R_{min}$). | SD, COV and R have a similar trend to that of the repeatability of concrete strength. |
| ASTM C 805 (2018) [52] | a. Standard deviation of the rebound results has a constant value independent of the properties of the actual concrete and the actual operator error,<br>b. Percentage points of the standardized ranges of N (μ,1) normal probability distribution | a. The standard deviation of the rebound index ($S_R$),<br>b. Coefficient of Variation of the rebound index ($CV_R$),<br>c. Range of rebound index ($R_r$) corresponding to test locations. | Absence of probability distribution of within standard test deviation of the rebound index or about its percentile level for which the value is given in the standard. |
| ASTM C 670 (2015) [53] | Application of the theory of standardized ranges ω for N (μ, 1) normal probability distribution populations for the determination of the multiplier applied to the maximum acceptable range. | Cumulative probability distribution function of the calculated studentized ranges ($øR = R_r/S_R$) to test locations with standardized ranges (ω) to n = 10 of N (μ,1). | Standard ranges usually cannot be applied for actual measurements, as real standard deviation is not known. |
| EN 12390-3 (2009) [54] | Coefficient of Variation of the rebound index could not be an acceptable estimate of the Coefficient of Variation of concrete compressive strength. | Precision (Normality range) of the compressive strength ($P_{fc}$) and rebound hammer ($P_R$) in percentage. | Two variables are entirely independent of each other, and no relationship is possible to be formulated between them. |
| IS 13311 1 P-II [55] | Based on the theory of B-Proceque manual (2003) of rebound hammer. | Some gaps can be found in the recommendations | They are suggested to be reconsidered- no amendments to date. |

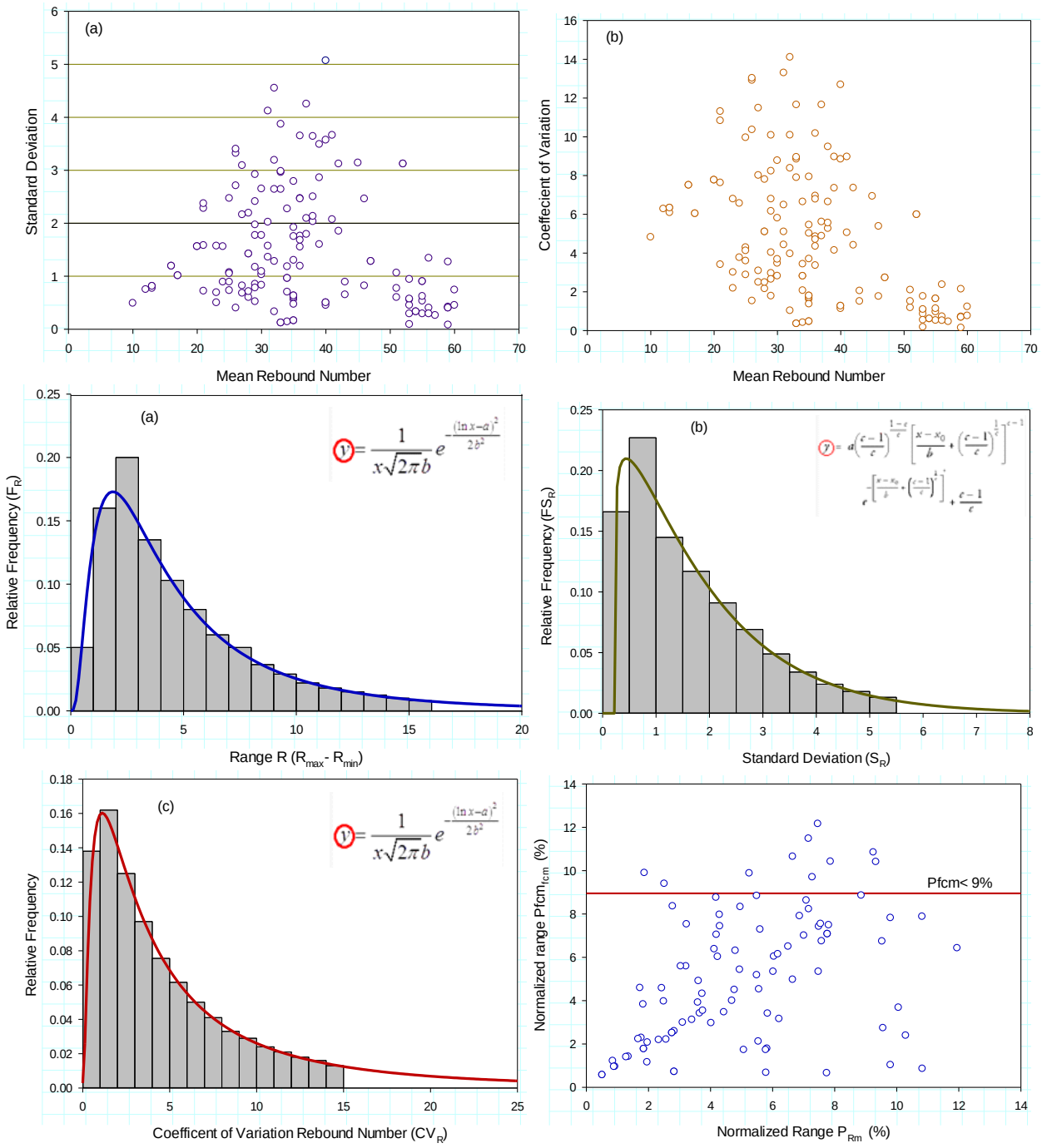



Fig. 3.3 Repeatability of concrete RH using comprehensive statistical analysis

Fig. 3.3 shows the graphical representation of the statistical analysis considering the within-test variation as the SD and COV over the mean rebound index. It recognizes that no consistent trend is observed, and a decreasing trend has been seen by the increasing average, as shown in Fig 3.3. The standard deviation or the COV of repeated tests by the same operator on the same material will be suitable for the characterization of repeatability.

The reliability of concrete compressive strength is acceptable only in the normalized range of less than 9 %. After considering the results of the present study, the 97 % (Pfc) results are less than 9 %. It indicates that the results obtained using locally available material can be precise and reliable according to EN 12390-3 [54].

According to ASTM C-805 [52] (three-parameter lognormal probability density function) with the best-fit curve for 534 test locations respectively. It is found that the three distribution (lognormal and Weibull probability density function) has a strong positive skewness

### 3.3. CONTRIBUTION 3- Evaluation of reliability of prediction model (Fitting and prediction Phase)

The assessment methodology is based on controlled parameters such as the number of test locations for cores (NT), within-test variability and NDT methods (RH, UPV and Combined Method (CM)) (Fig. 3.4).

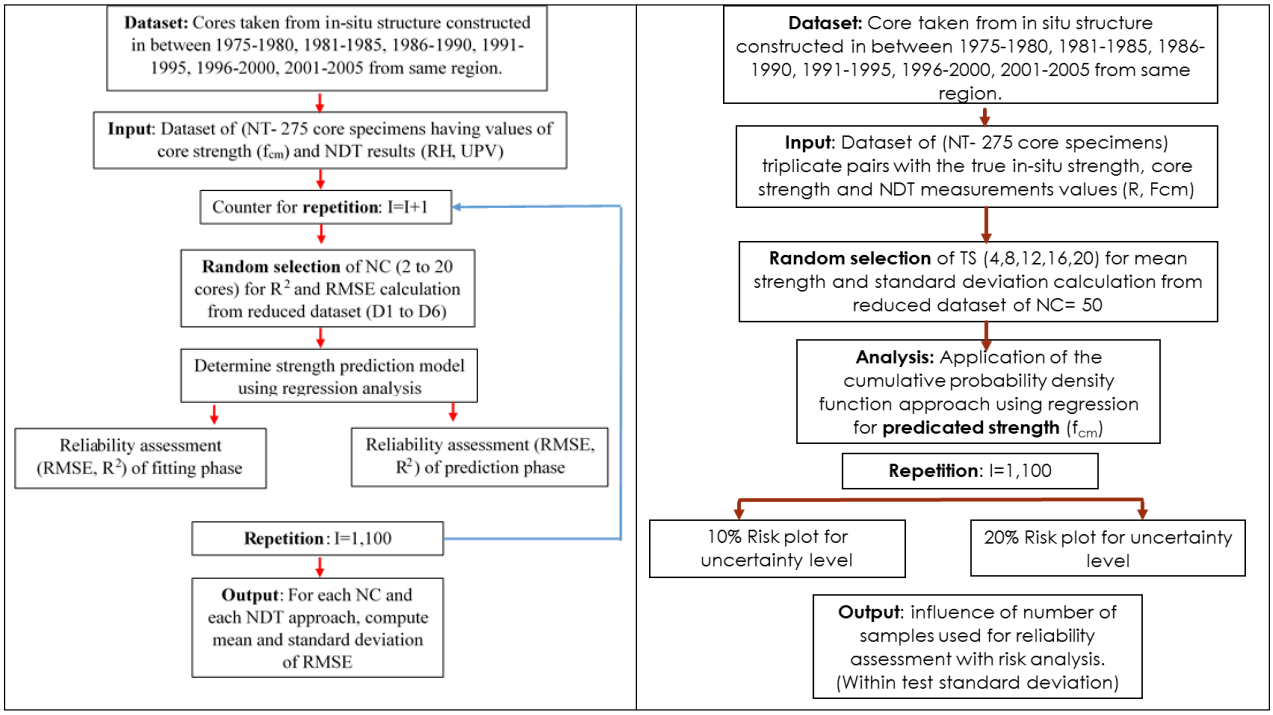

Dataset: Cores taken from in-situ structure constructed in between 1975-1980, 1981-1985, 1986-1990, 1991-1995, 1996-2000, 2001-2005 from same region.
Input: Dataset of (NT- 275 core specimens having values of core strength ($f_{cm}$) and NDT results (RH, UPV)
Counter for repetition: I=I+1
Random selection of NC (2 to 20 cores) for $R^2$ and RMSE calculation from reduced dataset (D1 to D6)
Determine strength prediction model using regression analysis
Reliability assessment (RMSE, $R^2$) of fitting phase
Reliability assessment (RMSE, $R^2$) of prediction phase
Repetition: I=1,100
Output: For each NC and each NDT approach, compute mean and standard deviation of RMSE
Dataset: Core taken from in situ structure constructed in between 1975-1980, 1981-1985, 1986-1990, 1991-1995, 1996-2000, 2001-2005 from same region.
Input: Dataset of (NT- 275 core specimens) triplicate pairs with the true in-situ strength, core strength and NDT measurements values (R, Fcm)
Random selection of TS (4,8,12,16,20) for mean strength and standard deviation calculation from reduced dataset of NC= 50
Analysis: Application of the cumulative probability density function approach using regression for predicated strength ($f_{cm}$)
Repetition: I=1,100
10% Risk plot for uncertainty level
20% Risk plot for uncertainty level
Output: influence of number of samples used for reliability assessment with risk analysis. (Within test standard deviation)

Fig. 3.4 Part- II Reliability of strength estimation using NDT methods, Part- III Within test variation (Uncertainty analysis)

Fig. 3.4 shows the flow chart of a process used in this work to evaluate the reliability. The accuracy evaluation is based on the data set of 275 core strength results obtained from the in-situ structures grouped by age (D1 to D6). Values obtained from the difference between calculated and observed results are strength values achieved by applying the same technique to a small set of cores. The core strength results were selected for each number of cores (NC) from within the group (D1 to D6). Core results were extracted from existing structures in terms of destructive and Non-destructive tests, as shown in Table 3.3. Author pointed out that uncertainties affect assessment, the structural concrete strength variation due to batch-to-batch (mix composition, compaction deficiency, different curing conditions), member-to-member (environmental conditions), within member (voids and cracks).

Table 3.3 Statistical database parameters based on year of construction

| Year | Statistical parameters | Diameter of Core (mm) | Height of Core (mm) | UPV (Km/Sec) | Rebound No | CCS (N/mm$^2$) |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| **1975-1980** | NC | 50 | 50 | 50 | 50 | 50 |
| | Range | 73.88-105.74 | 85.64-204.25 | 0.768-4.368 | 10.07-48.37 | 7.65-23.75 |
| | SD | 13.42 | 30.10 | 0.84 | 8.40 | 4.14 |
| | COV | 0.16 | 0.21 | 0.27 | 0.28 | 0.26 |
| **1981-1985** | NC | 50 | 50 | 50 | 50 | 50 |
| | Range | 73.64-105.50 | 85.27-204.25 | 0.976-4.078 | 15.08-50 | 6.16-25.83 |
| | SD | 15.73 | 29.92 | 0.82 | 9.38 | 5.33 |
| | COV | 0.19 | 0.21 | 0.29 | 0.28 | 0.35 |
| **1986-1990** | NC | 50 | 50 | 50 | 50 | 50 |
| | Range | 61.08-105.47 | 80.23-209.07 | 2.028-4.503 | 17.50-47.37 | 5.94-28.28 |
| | SD | 12.98 | 28.32 | 0.64 | 8.94 | 5.90 |
| | COV | 0.16 | 0.20 | 0.21 | 0.27 | 0.35 |
| **1991-1995** | NC | 25 | 25 | 25 | 25 | 25 |
| | Range | 73.53-105 | 74.38-200.30 | 1.516-4.409 | 12.37-50.9 | 9.37-21.28 |
| | SD | 0.36 | 22.82 | 0.66 | 10.58 | 2.93 |
| | COV | 0.00 | 0.17 | 0.21 | 0.29 | 0.18 |
| **1996-2000** | NC | 50 | 50 | 50 | 50 | 50 |
| | Range | 73.49-105.71 | 80.21-210.99 | 2.610-4.166 | 22.12-50.28 | 12-38.09 |
| | SD | 15.82 | 37.20 | 0.41 | 6.25 | 6.41 |
| | COV | 0.18 | 0.22 | 0.12 | 0.17 | 0.25 |
| **2000-2005** | NC | 50 | 50 | 50 | 50 | 50 |
| | Range | 73.04-74.94 | 87.26-147.87 | 0.875-4.098 | 17.05-47 | 5.96-24.98 |
| | SD | 0.47 | 18.02 | 0.69 | 8.07 | 4.72 |

Table 3.4 Best fit prediction models using single and combined NDT results

| | | | | |
|---|---|---|---|---|
| 1975 -1980 (D1) | UPV | $f_{cm} = 6.8454*V^{0.7359}$ | Power | 0.75 |
| | | $f_{cm} = 6.2165*e^{0.2885v}$ | Expo. | 0.73 |
| | RH | $f_{cm} = 1.4347*R^{0.7108}$ | Power | 0.72 |
| | | $f_{cm} = 6.7881*e^{0.0273R}$ | Expo. | 0.65 |
| | (UPV, RH) | $f_{cm} = 2.317*(R^{0.387})*(V^{0.546})$ | Power | 0.82 |
| | | $f_{cm} = 5.747*e^{0.013V} *e^{0.188R}$ | Expo. | 0.81 |
| 1981-1985 (D2) | UPV | $f_{cm} = 5.6741*V^{0.9236}$ | Power | 0.75 |
| | | $f_{cm} = 4.4843*e^{0.4039V}$ | Expo. | 0.79 |
| | RH | $f_{cm} = 0.4104*R^{1.0205}$ | Power | 0.74 |
| | | $f_{cm} = 4.3936*e^{0.0348R}$ | Expo. | 0.76 |
| | (UPV, RH) | $f_{cm} = 0.741*(R^{0.658})*(V^{0.655})$ | Power | 0.85 |
| | | $f_{cm} = 3.693*e^{(0.020V)} *e^{(0.241R)}$ | Expo. | 0.88 |
| 1986 -1990 (D3) | UPV | $f_{cm} = 3.0186*V^{1.5306}$ | Power | 0.75 |
| | | $f_{cm} = 3.4964*e^{0.4999V}$ | Expo. | 0.71 |
| | RH | $f_{cm} = 0.3306*R^{1.121}$ | Power | 0.72 |
| | | $f_{cm} = 4.8074*e^{0.0363R}$ | Expo. | 0.73 |
| | (UPV, RH) | $f_{cm} = 0.569*(R^{0.755})*(V^{0.677})$ | Power | 0.86 |
| | | $f_{cm} = 4.104*e^{(0.025R)}*e^{(0.187V)}$ | Expo. | 0.85 |
| 1991-1995 | UPV | $f_{cm} = 7.4362*V^{0.6951}$ | Power | 0.74 |

| | | | | |
|---|---|---|---|---|
| (D4) | | $f_{cm} = 7.4854*e^{0.2457V}$ | Expo. | 0.74 |
| | RH | $f_{cm} = 3.5129*R^{0.4308}$ | Power | 0.75 |
| | | $f_{cm} = 9.1285*e^{0.0156R}$ | Expo. | 0.78 |
| | (UPV,RH) | $f_{cm} = 4.032*(R^{0.254})*(V^{0.437})$ | Power | 0.82 |
| | | $f_{cm} = 7.398*e^{(0.010R)}*e^{(0.136V)}$ | Expo. | 0.86 |
| 1996 -2000 (D5) | UPV | $f_{cm} = 2.2338*V^{1.939}$ | Power | 0.74 |
| | | $f_{cm} = 3.3974*e^{0.5703V}$ | Expo. | 0.74 |
| | RH | $f_{cm} = 0.2604*R^{1.2758}$ | Power | 0.74 |
| | | $f_{cm} = 6.4351*e^{0.0373R}$ | Expo. | 0.72 |
| | (UPV, RH) | $f_{cm} = 0.814*(R^{0.506})*(V^{1.304})$ | Power | 0.82 |
| | | $f_{cm} = 4.122*e^{(0.015R)}*e^{(0.363V)}$ | Expo. | 0.81 |
| 2000 -2005 (D6) | UPV | $f_{cm} = 5.4942*V^{0.9874}$ | Power | 0.78 |
| | | $f_{cm} = 4.5742*e^{0.4112V}$ | Expo. | 0.80 |
| | RH | $f_{cm} = 0.3415*R^{1.091}$ | Power | 0.78 |
| | | $f_{cm} = 4.8052*e^{0.0344R}$ | Expo. | 0.76 |
| | (UPV, RH) | $f_{cm} = 0.879*(R^{0.633})*(V^{0.621})$ | Power | 0.86 |
| | | $f_{cm} = 4.305*e^{(0.018R)}*e^{(0.22V)}$ | Expo. | 0.87 |

The coefficients $R^2$ assess the goodness of fit, as shown in Table 3.6, but do not indicate the model's reliability when applied for strength prediction from future NDT tests for prediction intervals to several cores from 2 to 20. This study determined $R^2$ values for single and multiple NDT variables and two forms of a regression equation (Power and Exponential), as shown in Table 3.6 for twenty core results. Equations using one NDT variable (RH or UPV) provide a $R^2 > 0.70$, which is improved to $R^2 > 0.80$ when two NDT variables equations are used.

According to [56], RMSE used for estimation of discrepancy linked to the predicted values more explicitly (Eq. 1).

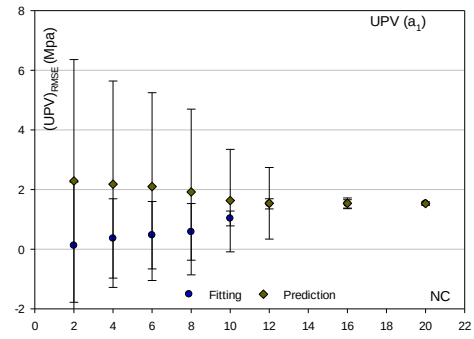
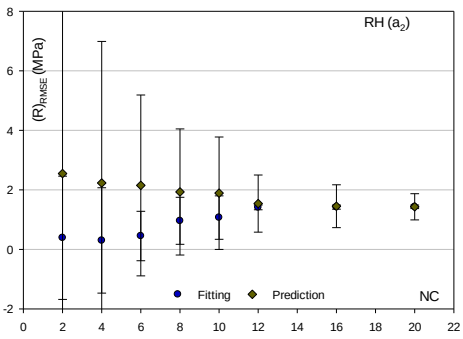
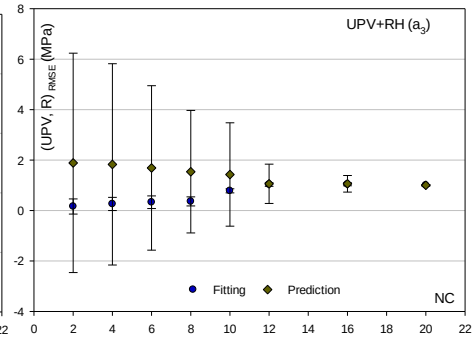
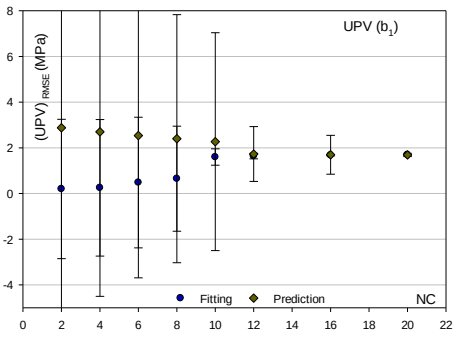
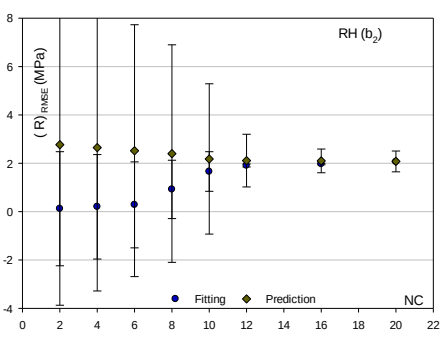
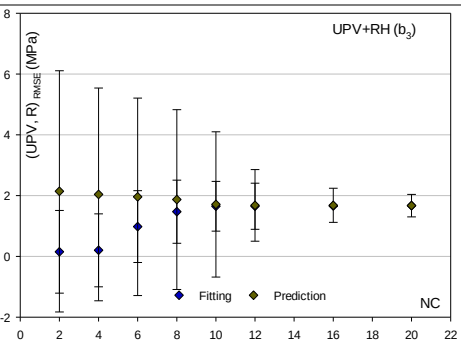
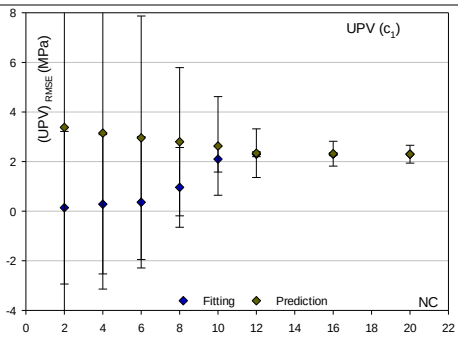
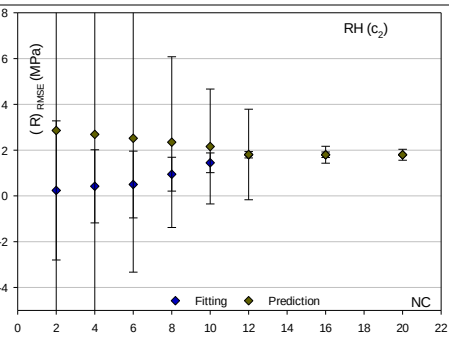
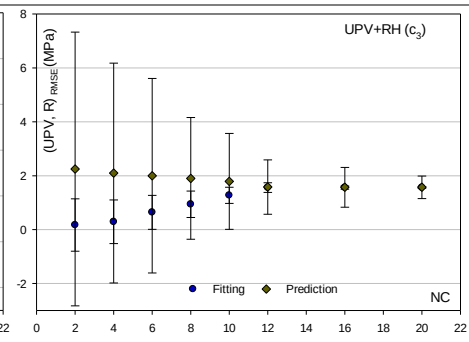
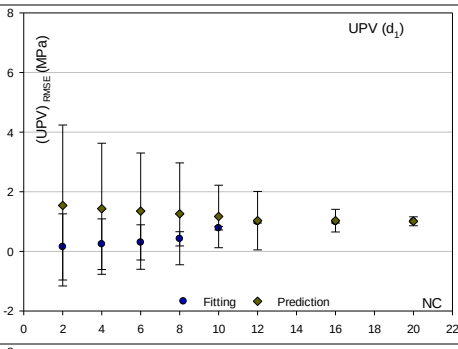
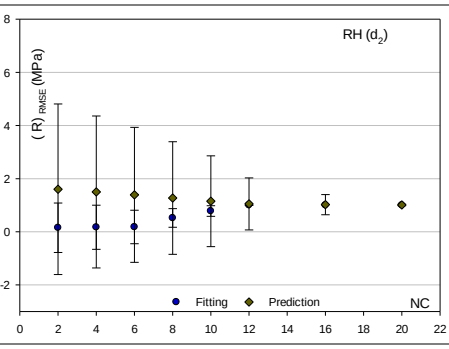
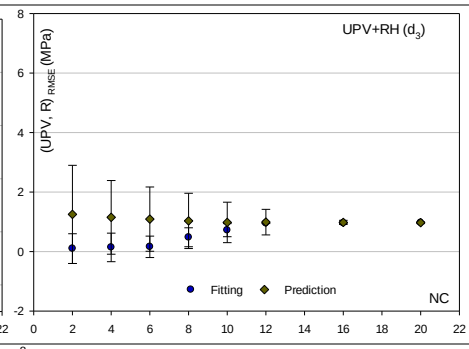
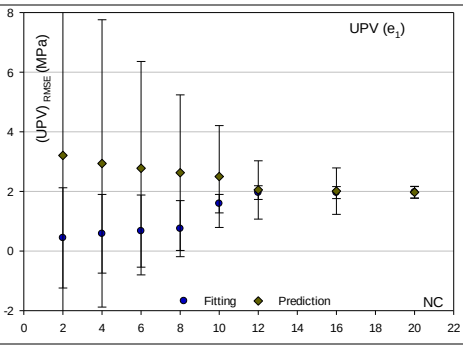
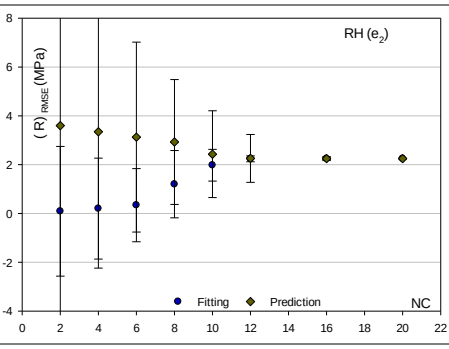
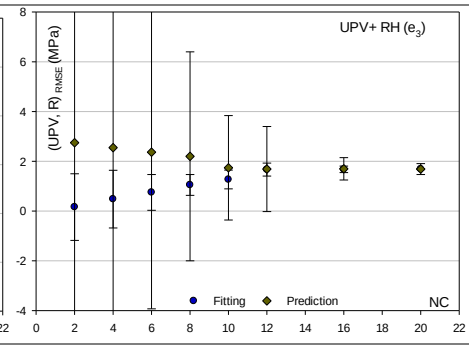
$$RMSE_{(fitted)} = \sqrt{\frac{\sum_{i=1}^{NC}(f_m - f_e)^2}{NC}} \quad \text{eq. (1)}$$

According to [57] statistics carried out a range of prediction indicators. The prediction error can be determined for (NT-NC) test locations using the following adjusted form of Eq. (2).

$$RMSE_{(predicated)} = \sqrt{\frac{\sum_{i=1}^{NT-NC}(f_m - f_e)^2}{NT-NC}} \quad \text{eq. (2)}$$

The $RMSE_{fit}$ and $RMSE_{pred}$ are shown in Fig. 3.5 as a function of the number of cores used to determine the prediction models using RH, UPV and combined methods. The vertical lines in Fig. 3.5 represent ±one standard deviation of the RMSE values obtained for the 100 iterations for each value of NC. The average value of $RMSE_{pred}$ is always higher than $RMSE_{fit}$. $RMSE_{fit}$ and $RMSE_{pred}$ are stabilized at 1.8 to 2 MPa for rebound hammer with age groups (D1-D6), respectively. In the case of UPV, $RMSE_{fit}$ and $RMSE_{pred}$ are stabilized at 1 to 2 MPa with age groups (D1-D6), respectively. Similarly, $RMSE_{fit}$ and $RMSE_{pred}$ results of age groups D1, D4 and D6 are stabilized at 1.0 MPa, and 1.8 MPa for age groups D2, D3 and D5, respectively, for NC values from 9 to 20.

$RMSE_{pred}$ is two times greater than $RMSE_{fit}$, in the case of low NC numbers. As NC varies, the values of $RMSE_{fit}$ and $R^2$ for UPV and RH are equivalent to the constant difference, as shown in Fig. 3.6.

| Y | UPV | RH | (UPV+RH) |
|---|---|---|---|
| 1975-1980 (D1) |  |  |  |
| 981-1985 (D2) |  |  |  |
| 1986-1990 (D3) |  |  |  |
| 1991-1995 (D4) |  |  |  |
| 1995-2000 (D5) |  |  |  |

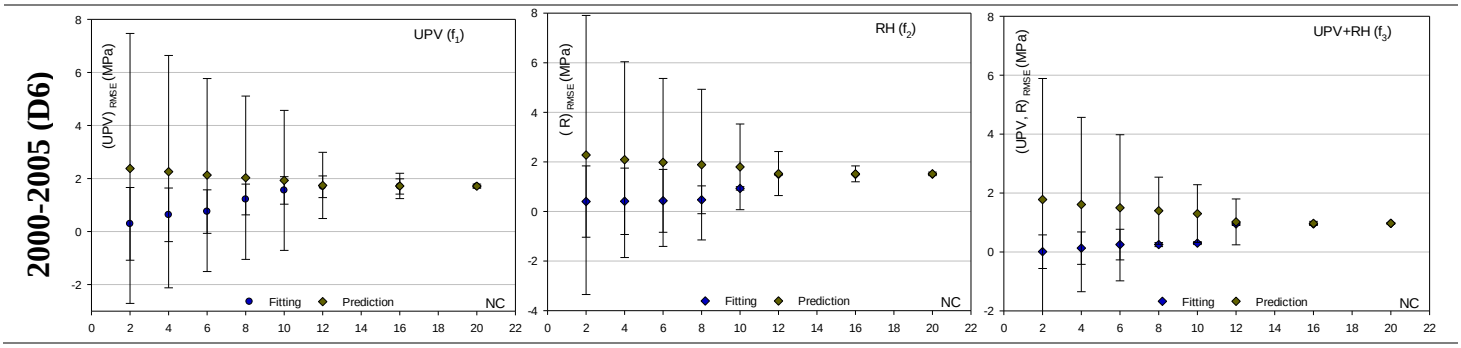



Fig. 3.5 RMSE (mean and SD) for fitting model and for future predictions as a function of number of points used to determine fitted model

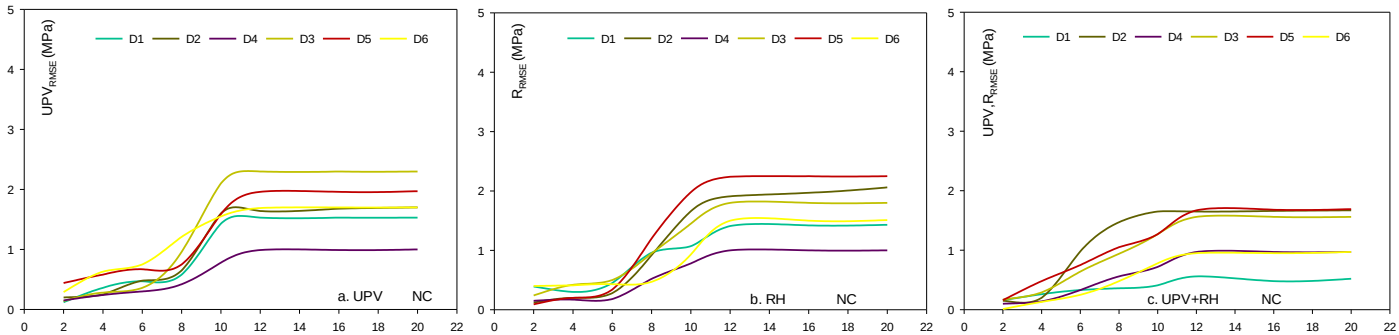



Fig. 3.6 Comparative analyses of $RMSE_{fit}$ vs the number NC for different ages (D1 to D6).

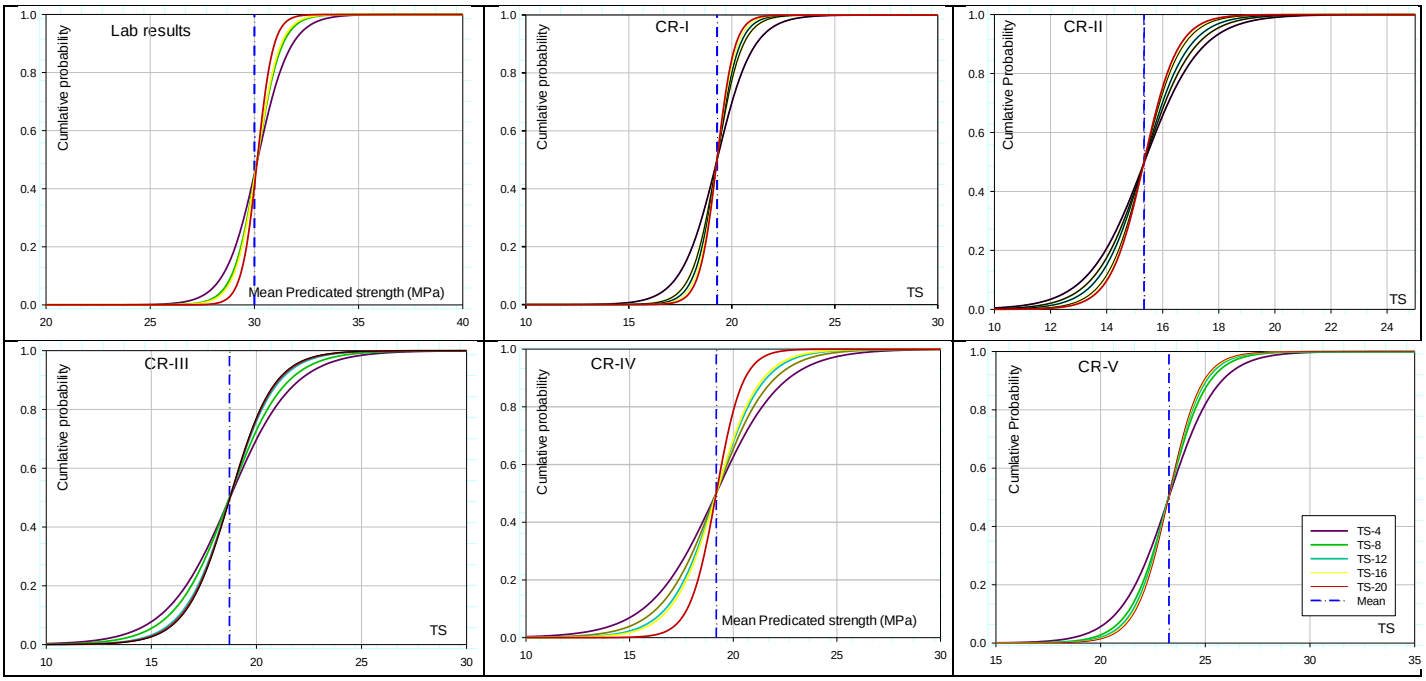



Fig. 3.7 Uncertainty plot corresponding to regression approach for each NC (Lab results, Core Results-I to V (Year))

The cumulative density function plot varies with NC (2 to 20) for mean strength estimation in the lab and core results. Reliability assessment is analyzed concerning the mean reference of corresponding NC values for compressive strength shown in Fig 3.7 with the blue vertical line. However, the difference between the uncertainty values decreases as NC increases and becomes negligible when NC > 10. This analysis indicates practical rules for defining the minimal number of cores required to reach significant reliability

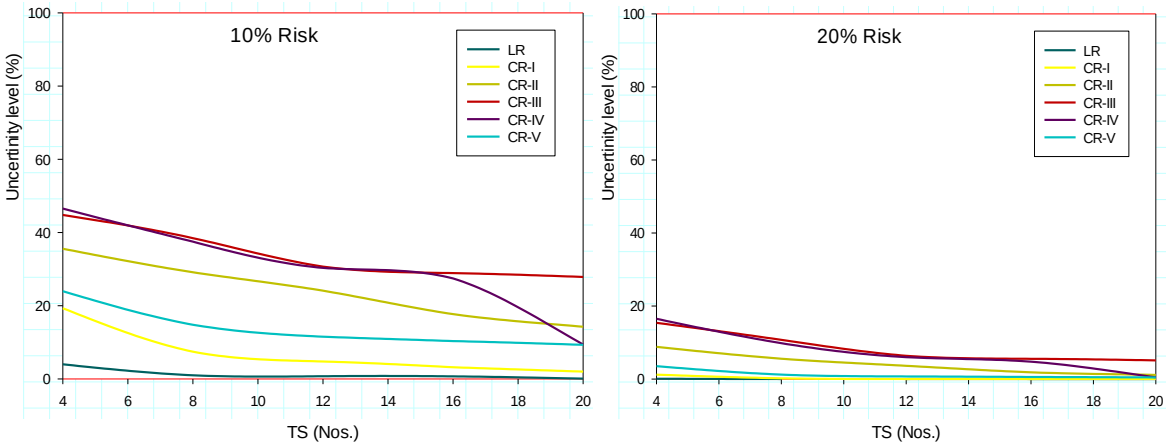



Fig. 3.8 Difference between the two (10% and 20%) risk plot illustrates the effect of standard deviation on the reliability assessment.

The difference between the 10 and 20% risk in the uncertainty plots illustrates the effect of standard deviation on the reliability assessment. Due to the identical values of each NC for the more variable dataset, the mean strength and standard deviation evaluation are less accurate. However, when the number of core samples increases, the actual difference between the uncertainty values reduces until it is insignificant at NC > 10 as shown in Fig. 3.8. Alwash et al. (2017) [33] focused on the role of regression and the Bi-objective approach for constructing the risk curves with an accepted uncertainty level (25%) for their variable dataset.

### 3.4. CONTRIBUTION 4- FEM analysis

In the present study, the development of a reduction coefficient curve for the rebound index, based on in-situ measurement of the carbonated layer thickness, has been carried out through the numerical simulation of the impact. Abaqus FEM with an explicit integration scheme and the Concrete Damaged Plasticity constitutive model to describe the inelastic behaviour of the carbonated concrete.

To optimize the computing time, the mechanical model of 3D Solid provided that the model was wide enough to reproduce the mechanical problem correctly. The geometry of the concrete cube has been taken 150mmx150mmx150mm. The concrete has been partitioned into two layers, one with fully carbonated and the other with non-carbonated concrete material properties shown in Table 3.6, representing the progress of carbonation development into the cube specimen. The mesh size is minimum for the first set of specimens, 0.3x0.3 mm, and 0.5x0.5mm for the second set of specimens. The impacting mass (Steel) has been modelled to reproduce the shape of the plunger of a Schmidt hammer. This steel plunger has been defined as a rigid body considering that it does not develop plastic deformations during impact. The impacting mass possesses an initial velocity V of 5.718 m/s to provide kinetic energy equal to 2.207 Nm, similar to the Schmidt hammer (Fig 3.9). The FEM analysis ran with consideration of the Dynamic Explicit model through parameters in Table 3.5.

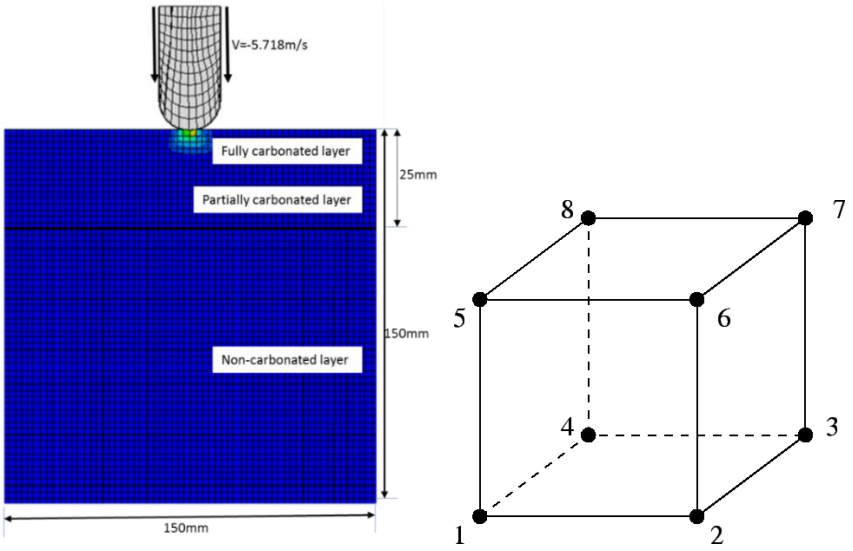



Fig. 3.9 a. Geometry of the concrete cube (3 carbonation layers) with impacting mass (Steel plunger) b. C3D8R Element

Table 3.5 Finite element model analysis- (Dynamic Explicit)

| | | |
|---|---|---|
| Geometry | Node and Element property definition: Solid | Part: Concrete cube, Steel Plunger<br>Units: (Cube-0.15x0.15x0.15mm) |
| | | **Pre Treatment** |
| Property | Material property definition: Concrete | Density (Kg/m$^3$), Young's Modulus (MPa), Poisson ratio, Compression and plastic damage |
| | Material property definition: Steel | Density (Kg/m$^3$), Young's Modulus (MPa), Poisson ratio, Damping |
| | Create and Assign section | Concrete cube, Steel Plunger (Selecting Region) |
| Assembly | Create Instance | Dependent (Mesh on Part), Translation of part |
| Step | Dynamic Explicit | Time period = 0.1 |
| | F-Output (Whole Model) | Stress, Energy, Displacement, Velocity |
| | H-Output (Whole Model) | Stress, Energy, Displacement, Velocity |
| Interaction | Contact property option | Tangential and Normal Behavior. (Interprop) |
| | General contact Explicit | All surface pairs (Propagated) |
| | Constraint (Rigid body) | Region type- Body elements, Reference point |
| Load | Boundary Condition (Table 3.8) (Dis/ Rotation) | (CSYS: U1,U2,U3.UR1,UR2,UR3=0) |
| | Predefined field (Velocity) | (Translational velocity: V1, V3=0, V2=-5.718) |
| Mesh | Seed part Instance | Global size= 0.0002 |
| | Mesh control | Element shape: Hex, Structured |
| | Assign Element type (Select Regions) | Element library: Explicit, Family: 3D stress, Geometric order: Linear Element Deletion: Yes **C3D8R**: An 8-node linear brick, reduced integration, hourglass control. |
| | **Analysis** | |
| Job | Job creation | Submission, Data Check, Monitoring |
| | **Post Treatment** | |

| | | |
|---|---|---|
| Output | Results (Curve, X-Y data) (Fig 3.10) | S11- Vertical stress, S22- Circumfertinal stress, S33- Radial stress, Energy- Total, Kinetic, Plastic, Deformation- Elastic, Plastic |

Table 3.6. Mechanical properties of concrete

| Properties of Concrete | Non-carbonated concrete | Fully-carbonated concrete |
|---|---|---|
| Young's modulus Eo (MPa) | 18000 | 27000 |
| Poisson's ratio (ν) | 0.15 | 0.15 |
| Density, ρ (Kg/m$^3$) | 2300 | 2400 |
| Dilation angle = volume strain/ shear strain (ψ) | 37 | 37 |
| Flow potential eccentricity (ε) | 0.1 | 0.1 |
| Equi-biaxial compressive yield stress / initial uniaxial compressive yield stress (σb0/σc0) [Kupfer et al.] | 1.16 | 1.16 |
| Viscosity parameter | 0 | 0 |
| Weight factors wt and wc | 0 | 0 |
| K | 0.79 | 0.79 |
| Rayleigh damping parameters | | |
| α | 2134.7 | 2134.7 |
| β | 1.096x10-7 | 1.096x10-7 |

Table 3.7. Concrete damaged plasticity parameters of FEM

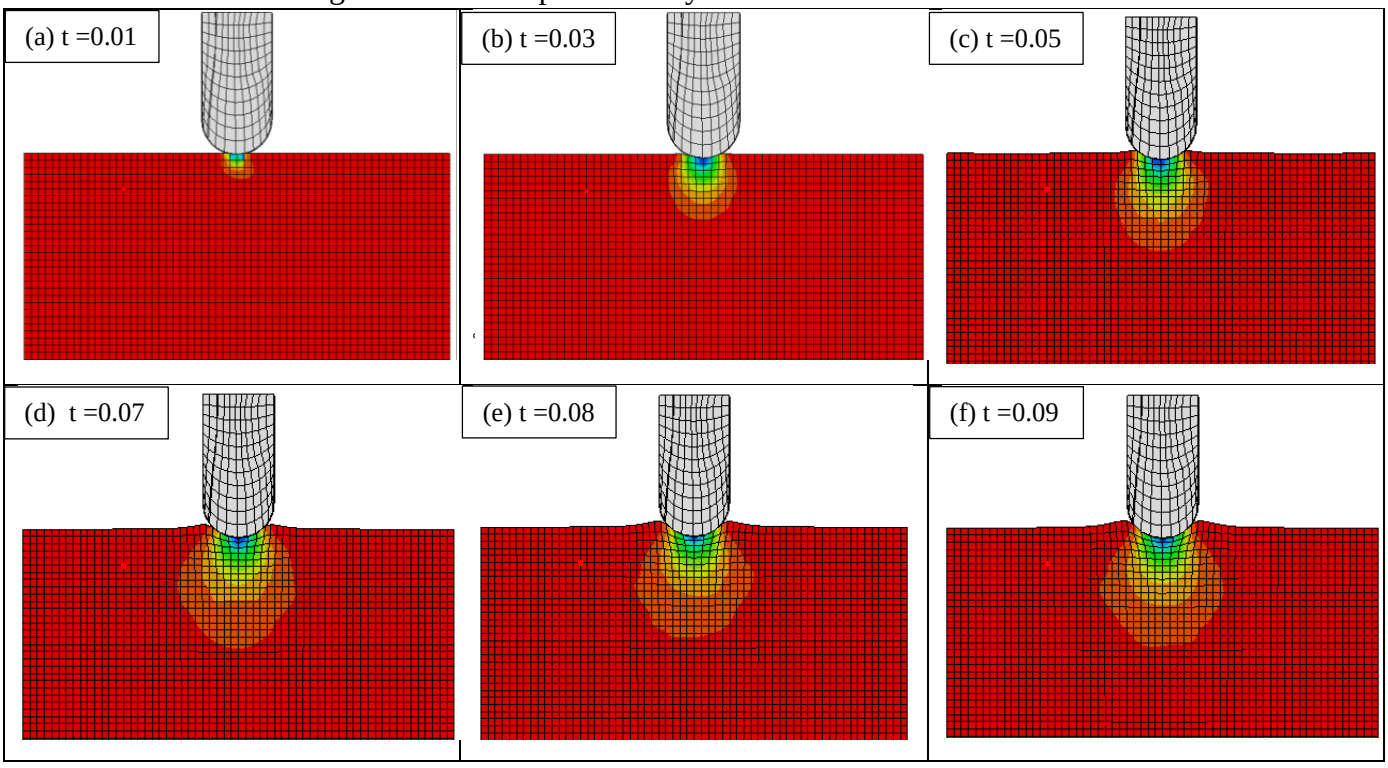
| Non-carbonated concrete | | | | Fully-carbonated concrete | | | |
|---|---|---|---|---|---|---|---|
| Concrete compressive behavior | | Concrete compression damage | | Concrete compressive behavior | | Concrete compression damage | |
| Yield stress, $\sigma_c$ (MPa) | Inelastic strain εin= εc - σc/Eo ($10^{-4}$) | Damage parameter [dc= 1-($\sigma_c/\sigma_{cu}$)] | Inelastic strain ($10^{-4}$) | Yield stress, $\sigma_c$ (MPa) | Inelastic strain εin= εc - σc/Eo ($10^{-4}$) | Damage parameter [dc= 1-($\sigma_c/\sigma_{cu}$)] | Inelastic strain ($10^{-4}$) |
| 10.2 | 0 | 0 | 0 | 25.5 | 0 | 0 | 0 |
| 12.8 | 0.773 | 0 | 0.773 | 32 | 0.057 | 0 | 0.057 |
| 15 | 1.735 | 0 | 1.735 | 37.5 | 0.414 | 0 | 0.414 |
| 16.8 | 2.886 | 0 | 2.886 | 42 | 1.0687 | 0 | 1.068 |
| 18.2 | 4.226 | 0 | 4.226 | 45.5 | 2.022 | 0 | 2.022 |
| 19.2 | 5.754 | 0 | 5.754 | 48 | 3.275 | 0 | 3.275 |
| 19.8 | 7.471 | 0 | 7.471 | 49.5 | 4.827 | 0 | 4.827 |
| 20 | 9.377 | 0 | 9.377 | 50 | 6.677 | 0 | 6.677 |
| 19.8 | 11.471 | 0.01 | 11.471 | 49.5 | 8.827 | 0.01 | 8.827 |
| 19.2 | 13.754 | 0.04 | 13.754 | 48 | 11.275 | 0.04 | 11.275 |
| 18.2 | 16.226 | 0.09 | 16.226 | 45.5 | 14.022 | 0.09 | 14.022 |
| 16.8 | 18.886 | 0.16 | 18.886 | 42 | 17.068 | 0.16 | 17.068 |
| 15 | 21.735 | 0.25 | 21.735 | 37.5 | 20.413 | 0.25 | 20.413 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 12.8 | 24.773 | 0.36 | 24.773 | 32 | 24.057 | 0.36 | 24.057 |
| 10.2 | 28 | 0.49 | 28 | 25.5 | 28 | 0.49 | 28 |
| 7.2 | 31.415 | 0.64 | 31.415 | 18 | 32.241 | 0.64 | 32.241 |
| 3.8 | 35.018 | 0.81 | 35.018 | 9.5 | 36.781 | 0.81 | 36.781 |
| Concrete tensile behavior | | Concrete tension damage | | Concrete tensile behavior | | Concrete tension damage | |
| Yield stress (MPa) | Cracking Strain (10-4) | Damage parameter [dt= 1-(σt/σtu)] | Cracking strain | Yield stress (MPa) | Cracking Strain (10-4) | Damage parameter [dt= 1-(σt/σtu)] | Cracking strain |
| **2** | 0 | 0 | 0 | 5 | 0 | 0 | 0 |
| **0.02** | 9.433 | 0.99 | 9.433 | 0.05 | 0.001 | 0.99 | 0.001 |

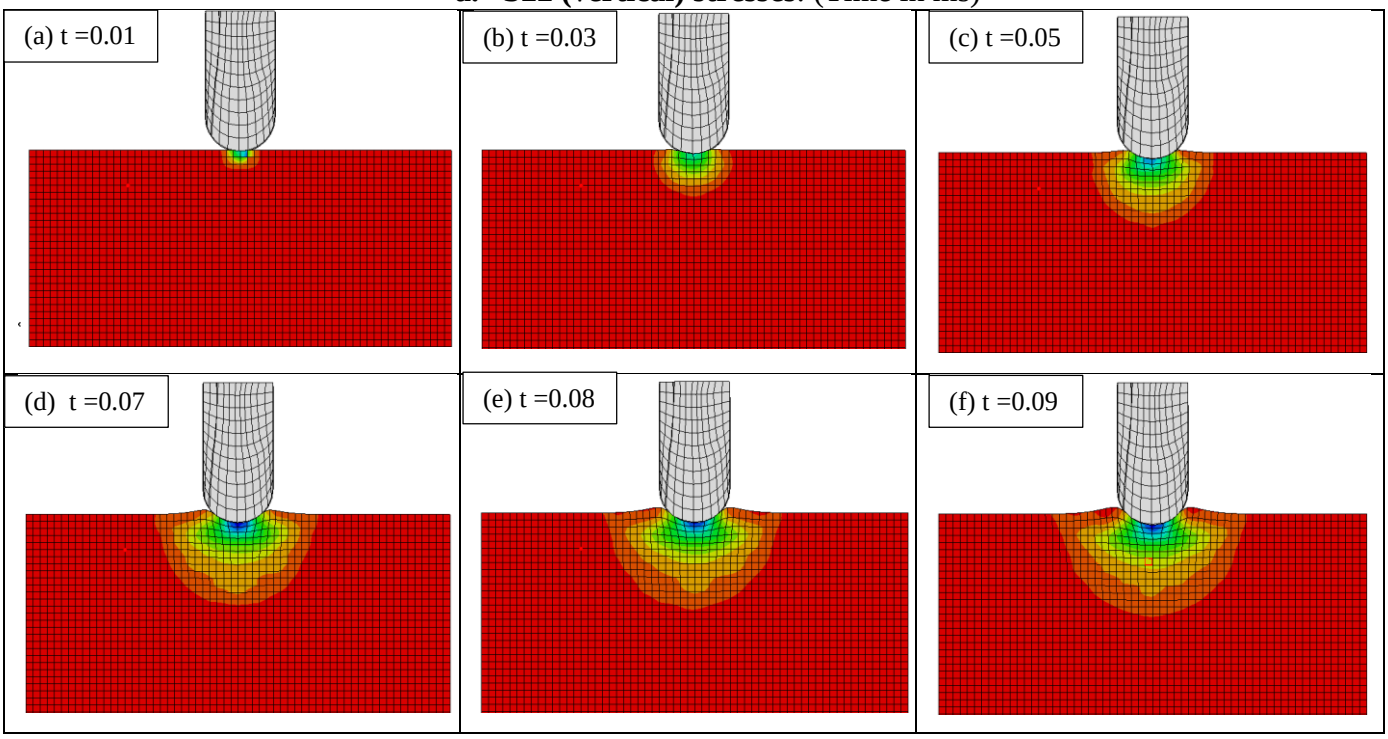
Table 3.8. Load and Boundary condition for FEM analysis

| | |
|---|---|
| (Displacement/ Rotation) | $U_1,U_2,U_3.UR_1,UR_2,UR_3=0$) |
| Translational velocity | $V_1$, $V_3=0$, $V_2=-5.718$m/s |
| Cube is restrained (bottom) | X, Y, Z Directions on nodes |
| The impact mass is applied | Y Directions |
| Element | C3D8R |
| No. of Elements | 126067 |
| No. of Nodes | 133959 |
| Output | S22 (vertical), S33 (circumferential), S11 (radial), S (mises) stresses (Fig. 6.34 (a, b, c)). |

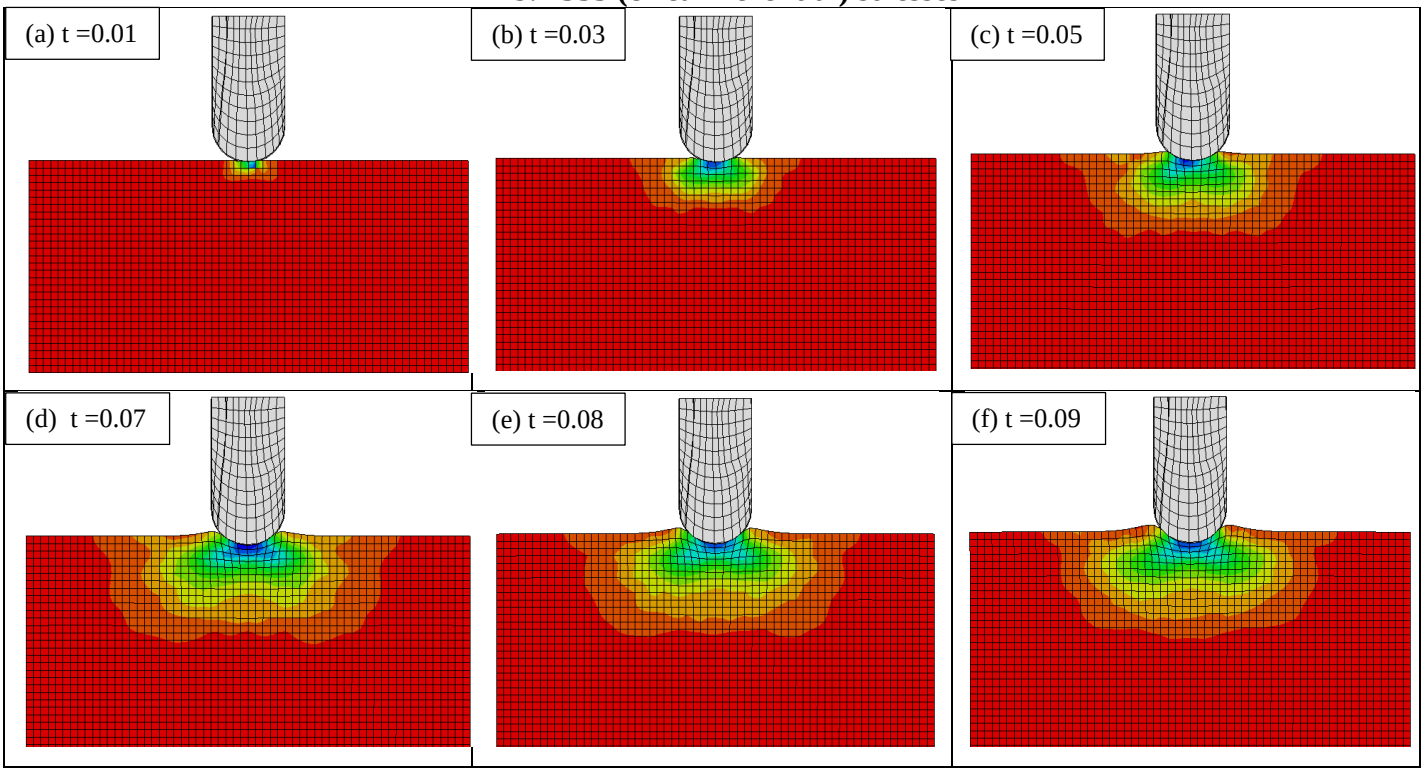
Images of vertical, circumferential and radial stresses are shown in Fig. 3.10. The high compressive stresses reached during the numerical simulations of the impact are consistent with the core strength measured experimentally.



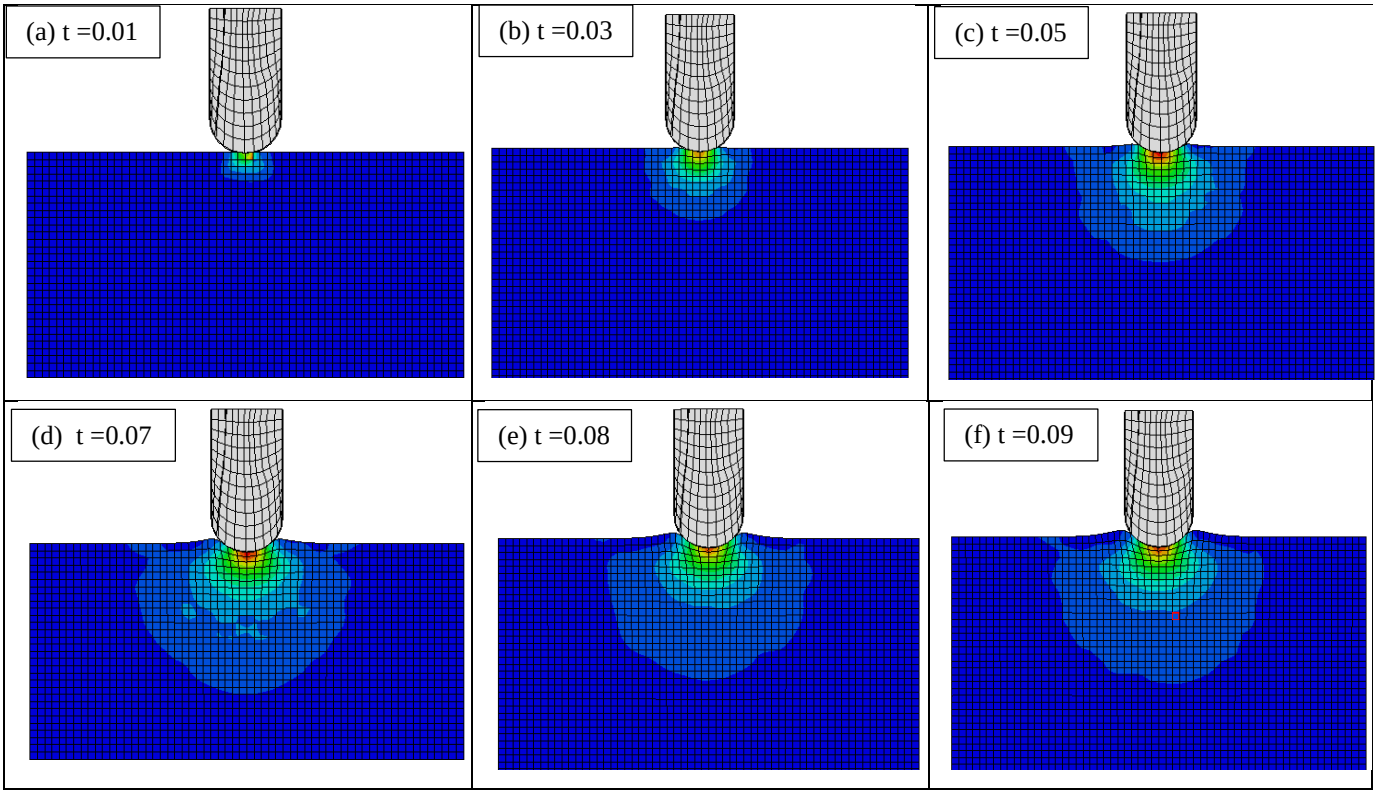
**a. S22 (vertical) stresses**: (Time in ms)




**b. S33 (circumferential) stresses**




**c. S11 (radial) stresses:**




**d. S (Mises) stresses**

Fig. 3.10 a. S22 (vertical) stresses b. S33 (circumferential) stresses c. S11 (radial) stresses d. S (Mises) stresses

Rebound number have been obtained for different carbonation depth ($x_c$) with consideration of carbonated concrete properties. Rebound coefficient (Q) in terms of the ratio of the velocities of impacting mass just after and just before the impact, and Rebound number (R) in terms of displacement. For a given concrete strength the rebound number R is a function of only $x_c$, i.e. $R=R(x_c)$, so the values of the correction coefficient for that strength are given by the Eq.3.

$k_c(x_c)= R(0)/ R(x_c)$. Eq.3

The values of $k_c$ have been subsequently fitted using the eq. 4.

Present study $c_f = 0.6436 * e^{\frac{2.0843}{x_c+4.7491}}$ Eq.4

The results of the finite element modelling have been used to establish an empirical relation that expresses the value of the reduction coefficient to be applied to the rebound index measured on carbonated concrete. It shows that the rebound index (R) does not change significantly for carbonation depth greater than 25 mm. Carbonation levels ranging from 10 mm to 30 mm are shown in the highest percentage at various aged structures. Fig. 3.11 (a) depicts the general trends of the reduction coefficients for a specific carbonation depth; the higher the strength of the concrete, the lower the reduction coefficient to be applied to the observed R-value. These results have been compared with experimental findings of Breccolotti [4] and Kim [5]. The comparison shows a good correlation between the fitted and the predicted results. Nevertheless, some differences have been noticed in the range for carbonation depth of 7 to 12 mm. Reduction coefficient curve according to influencing parameters (carbonation depth and elevated temperature) is shown in Fig. 3.11(b). Breccolotti [4] used axisymmetric

model for impact phenomena by FEM analysis. Lee, and Suraneni [58], used both Machine learning algorithms and FEM analysis for accurate carbonation progress predictor.

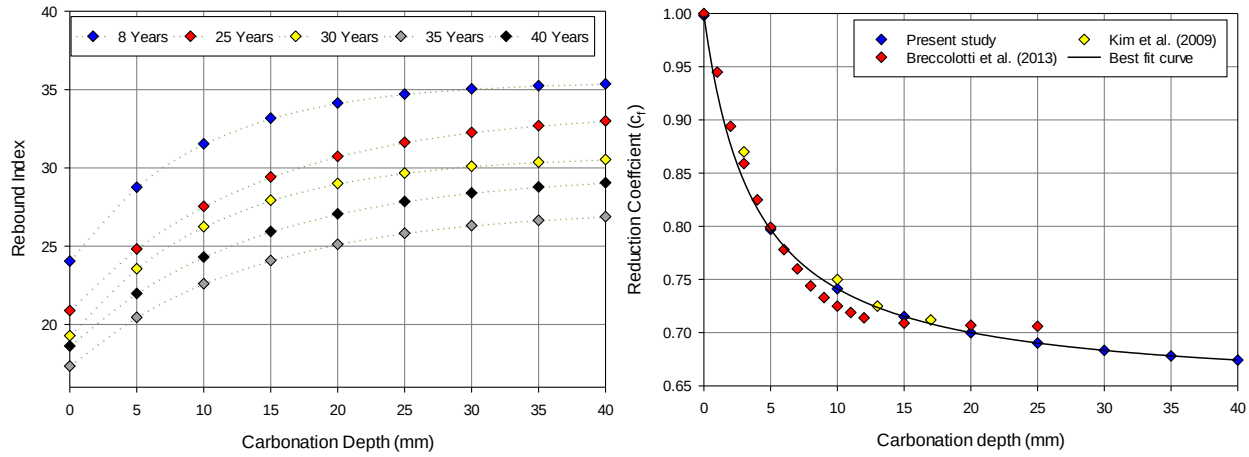



Fig. 3.11 a) Carbonation depth vs. Rebound Index (Empirical relation) b) Comparative analysis of reduction coefficient curve derived by researchers

### 3.5. CONTRIBUTION 5- ANFIS/ ANN model (Estimation of carbonation depth)

In the present study, a structural inspection of existing carbonated structures with ages ranging from 2 to 40 years has been performed to estimate the carbonation depth. The results of core compressive strength, Rebound index and core height and diameter ratio were measured at 186 points of carbonated structures. The level of carbonation depth is related to factors such as h/d ratio, equivalent cube strength and rebound index of a core specimen. These factors were considered while predicting the carbonation depth using the ANFIS system. This system is based on the result dataset obtained from field investigation, and the accuracy of the ANFIS system is compared with measurement results obtained from the destructive and non-destructive applications. Bell shape fuzzy sets are used in this work, which provides higher accuracy with ANFIS training.

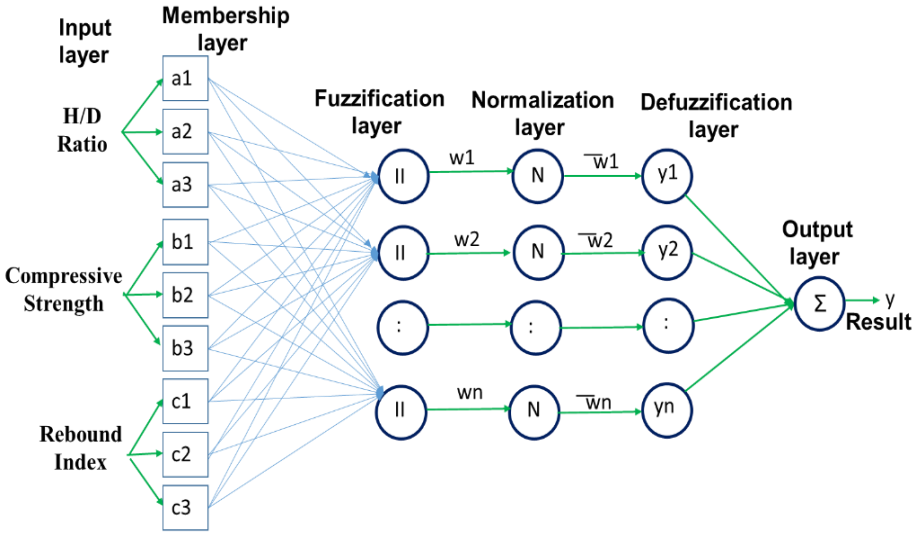


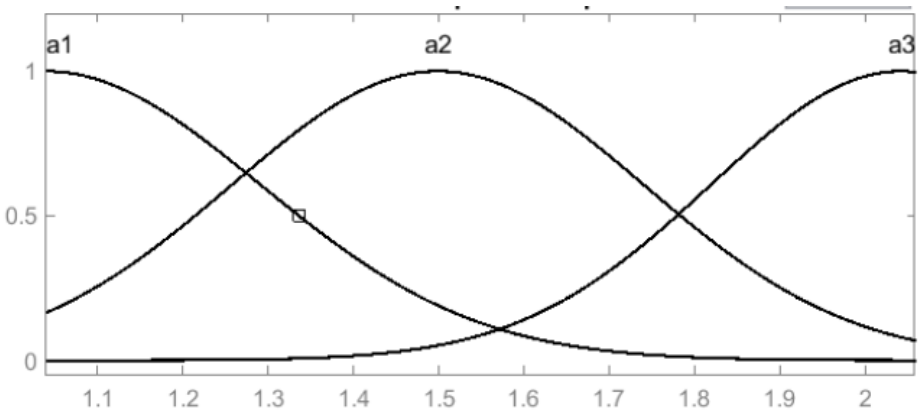

Fig. 3.12 ANFIS network in terms of layers

ANFIS is a method for optimizing premise and consequent parameters in the Sugeno fuzzy inference system by introducing a training algorithm (Fig.3.12). In this study, a 5-layer ANFIS structure was applied, as shown in Table 3.9. Sugeno ANFIS is used to predict output values for new input values by constructing rules based on known data, where all inputs and outputs are fuzzy values assigned to crisp values. The membership function indicates how much of a variable belongs to a fuzzy set, a subset of a crisp set. Each element in the crisp set represents its degree of belonging to any set as 0 or 1, but the degree in the fuzzy set is expressed as a number between 0 and 1. As a result, all options may be examined by defining the scenario of totally belonging as 1.0, the case of not belonging at all as 0, and the case of a 50% possibility of belonging as 0.5.

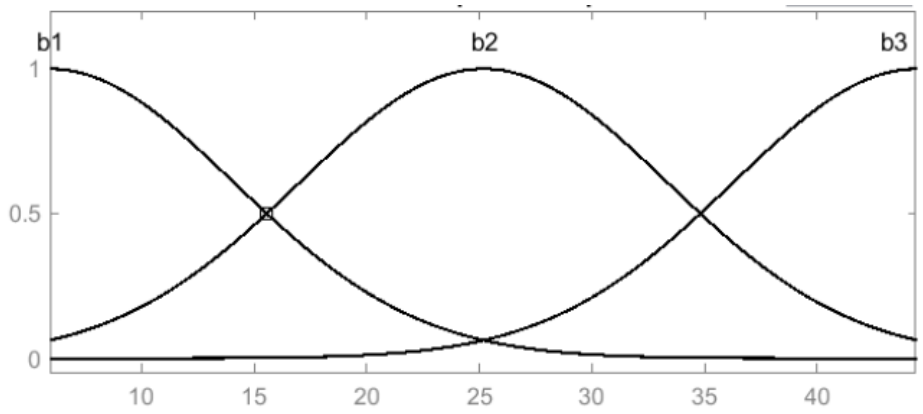
Table 3.9. Five-layer ANFIS structure (Sugeno fuzzy inference system)

| **Layer** | **Membership function, Input, Output parameters** (Fig. 3.12) |
|---|---|
| Layer 1 | ANFIS's accuracy improves after training using a bell-shaped fuzzy set.<br>Input parameters: xi, Premise parameters: xc, xq, xw |
| Layer 2 | Four input parameters govern each of the three fuzzy sets. Fuzzy rules are made up of all of the input parameters. Unlike the input component, which is built up of fuzzy sets, Sugeno fuzzy inference assumes that the output component is linear.<br>Input Coefficient: Age of structure (T), Core Height and Diameter ratio (H/D Ratio), Compressive Strength (fcm), Carbonation depth (Cd)<br>Consequent parameters: a, b, c, d (constant estimated by Least square method)<br>Output: Calculate membership function of each fuzzy sets by T norms method (Firing Strength) |
| Layer 3 | The membership function of fuzzy rules is normalized.<br>De-fuzzification utilizing the centroid of area approach to normalize the sum of firing strengths determined using the equation proposed in layer 2 and therefore generate a corresponding value using the normalized firing strength as a weight factor. |
| Layer 4 | The modified rule (yi) that represents the normalized firing strength is output. |
| Layer 5 | Defuzzifies the Layer 4 result, as well as the rebound index (yANFIS), from which many parameters may be computed (Fig. 3.13). |

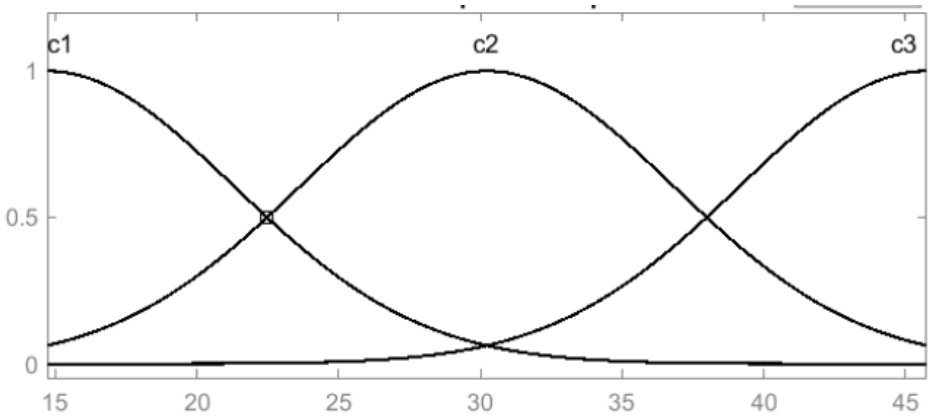
The membership functions of the fuzzy sets Fhdk, and Frk on the carbonation depth are $\mu$fcmk, $\mu$hdk, and $\mu$rk, respectively, as illustrated in Fig. 3.13.




a. Membership function- H/D Ratio




b. Membership function- Compressive strength (FCM)




c. Membership function- Rebound Index (R)

Fig. 3.13 Fuzzy sets of input parameters

Cho et al. [39] focused, 729 training rules were used for eight existing buildings dataset for estimation of carbonation depth. Malami et al. [40] study effect of carbonation with consideration of age, compressive strength, current density and carbonation constant. Comparative analysis of different models used in his study are well reflected the combined effects of carbonation diffusion coefficient on carbonation depth of existing structures.

The fifth objective also focused on the effect of Carbonation depth on the Rebound index by ANN Analysis. Data prediction using an ANN tool was optimized by feed-forward back prop Network training on existing structural inspection data as three input parameters, H/D ratio, FCM, and RI, shown in the training algorithm. Properties of the Neural Network are shown in Table 3.10.

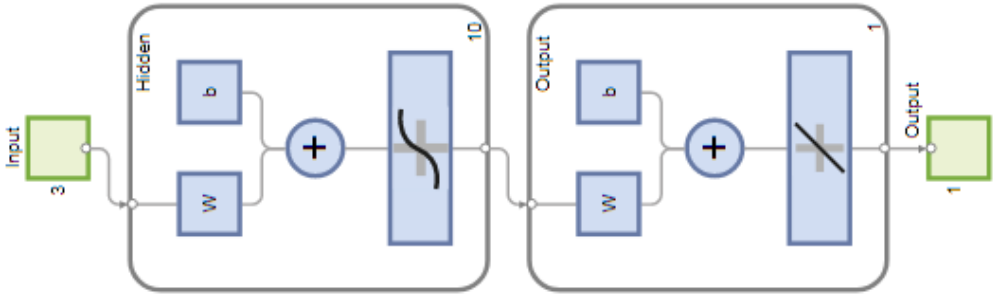



Fig. 3.14 Training algorithm (Output- Carbonation depth)

Table 3.10 Properties of the Neural Network (output- Carbonation Depth)

| Input parameters | Core results-H/D ratio, FCM, RI | Lab results- Cement Type, Compaction methods, Curing conditions, W/C ratio, Elevated temperature |
|---|---|---|
| Target | Carbonation depth | Rebound Index |
| Network Type | Feed-Forward Back propagation | Feed-Forward Back propagation |
| Hidden Neurons | 10 | 10 |
| Training algorithm | Levenberg-Marquardt | Levenberg-Marquardt |
| Training function | Trainlm | Trainlm |
| Adaption function | Learngdm | Learngdm |
| Transfer function | TANSIG | TANSIG |

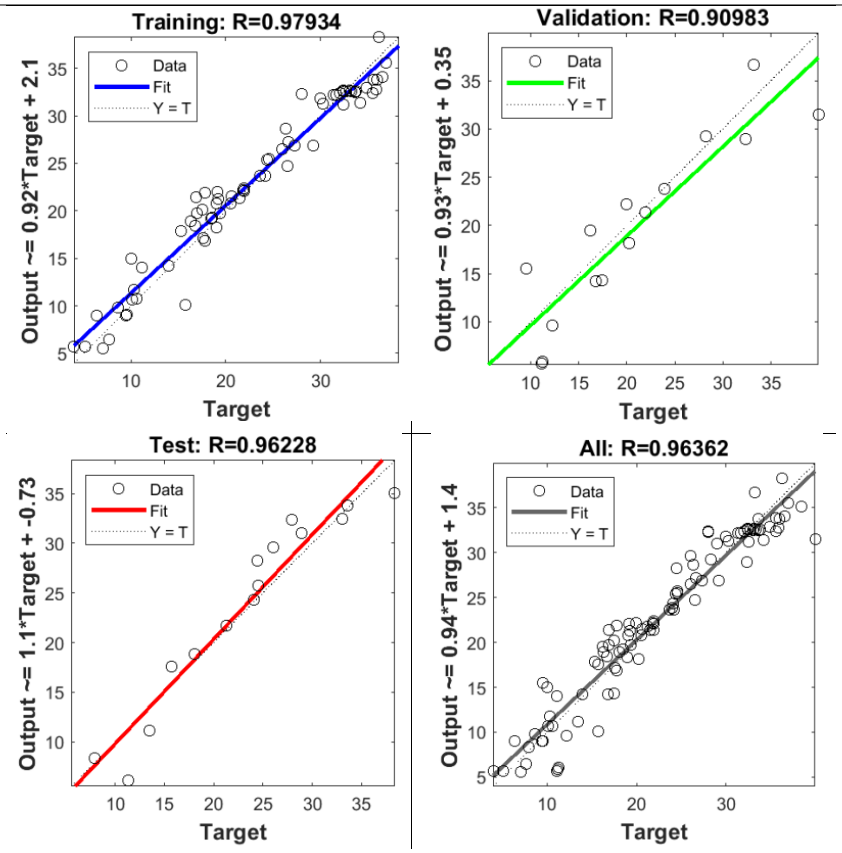



Fig. 3.15 Training, testing and validation output (Carbonation depth)

Trainlm as training function that updates weight and bias values according to Levenberg-Marquardt optimization in MATLAB achieved mean squared error shown in Table 3.11.

Table 3.11 Statistical performance indicators (ANNCD and ANNRI model)

| Statistical performance indicators | | ANN- Cd | ANN-RI |
|---|---|---|---|
| R2 | Training | 0.979 | 0.933 |
| | Testing | 0.962 | 0.939 |
| MSE | Training | 0.39 | 0.987 |
| | Testing | 0.956 | 1.251 |

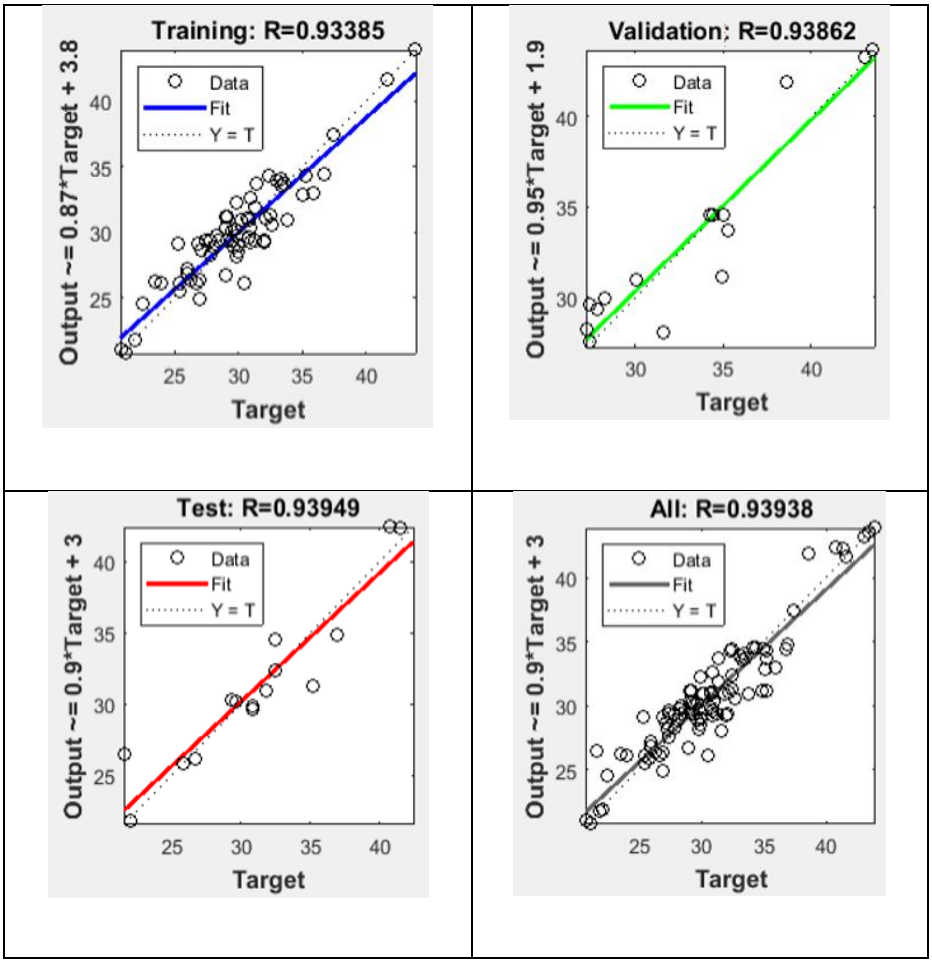



Fig.3.16 Training, testing and validation output (Rebound index)

### 3.6. CONTRIBUTION 6- Development of reduction coefficient for rebound index

The general trend of the results is shown in Table 3.12, for influencing factors, the higher the strength of the concrete, the lower the reduction coefficient to be applied to the measured R value. Table 10 illustrates that, the reduction coefficient applied for reliability estimation of strength with consideration of various factors. The range of reduction coefficient for carbonation effect (Fig 3.17a) is in between 0.63 to 1.0. The range of reduction coefficient for factors (type of cement used, curing condition and compaction deficiency (Fig 3.17c) is in between 0.81 to 1.0. Similarly, range of reduction coefficient for elevated temperature (Fig 3.17b) is very low in between 0.9 to 1.0.

Table 3.12. Reduction coefficient for different influencing factors

| Sub | Rebound Index | 20 | 22 | 24 | 26 | 28 | 30 | 32 | 34 | 36 | 38 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Type of Cement** | | | | | | | | | | | |
| Ultra $M_{20}$ | $0.0004x^2 - 0.0317x + 1.4687$ | 1.000 | 0.975 | 0.950 | 0.930 | 0.910 | 0.895 | 0.880 | 0.875 | 0.870 | 0.871 |
| Ultra $M_{25}$ | $0.0003x^2 - 0.0257x + 1.3765$ | 1.000 | 0.980 | 0.960 | 0.945 | 0.930 | 0.915 | 0.910 | 0.904 | 0.902 | 0.902 |
| Birla $M_{20}$ | $0.0001x^2 - 0.0108x + 1.1669$ | 1.000 | 0.990 | 0.980 | 0.970 | 0.960 | 0.955 | 0.950 | 0.940 | 0.940 | 0.935 |
| Birla $M_{25}$ | $0.0001x^2 - 0.012x + 1.1818$ | 1.000 | 0.990 | 0.980 | 0.970 | 0.965 | 0.950 | 0.950 | 0.945 | 0.940 | 0.940 |
| **Compaction method** | | | | | | | | | | | |
| Vibratory | $0.0002x^2 - 0.0147x + 1.2186$ | 1.000 | 0.990 | 0.980 | 0.970 | 0.960 | 0.950 | 0.945 | 0.943 | 0.942 | 0.942 |
| Manual | $0.0004x^2 - 0.0287x + 1.4179$ | 1.000 | 0.980 | 0.950 | 0.930 | 0.920 | 0.913 | 0.900 | 0.895 | 0.890 | 0.890 |
| No | $0.0007x^2 - 0.0514x + 1.7399$ | 1.000 | 0.950 | 0.910 | 0.880 | 0.860 | 0.840 | 0.823 | 0.812 | 0.811 | 0.810 |

| Curing condition | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Water | $0.0002x^2 - 0.0148x + 1.2187$ | 1.000 | 0.990 | 0.980 | 0.970 | 0.960 | 0.950 | 0.945 | 0.943 | 0.942 | 0.942 |
| Air | $0.0007x^2 - 0.0466x + 1.6639$ | 1.000 | 0.955 | 0.920 | 0.890 | 0.870 | 0.860 | 0.850 | 0.845 | 0.840 | 0.835 |
| **Carbonation** | | | | | | | | | | | |
| **Year** | **CD** | **5** | **10** | **15** | **20** | **25** | **30** | **35** | **40** | | |
| 8 | $1.254*Exp(X_1*-0.009)*Exp(X_2*-0.013)$ | 0.836 | 0.762 | 0.725 | 0.704 | 0.693 | 0.686 | 0.682 | 0.68 | | |
| 25 | | 0.842 | 0.758 | 0.71 | 0.68 | 0.66 | 0.647 | 0.639 | 0.633 | | |
| 30 | | 0.819 | 0.735 | 0.69 | 0.665 | 0.65 | 0.641 | 0.635 | 0.632 | | |
| 35 | | 0.848 | 0.768 | 0.72 | 0.691 | 0.672 | 0.659 | 0.651 | 0.645 | | |
| 40 | | 0.848 | 0.766 | 0.718 | 0.688 | 0.669 | 0.656 | 0.647 | 0.641 | | |
| **Temperature** | | | | | | | | | | | |
| **Grade** | **Temperature** | **0** | **200** | **400** | **600** | **800** | | | | | |
| HC $M_{20}$ | $1E-07x^2 - 9E-05x + 0.9998$ | 1 | 0.985 | 0.98 | 0.981 | 0.98 | | | | | |
| CC $M_{20}$ | $1E-07x^2 - 9E-05x + 0.9981$ | 1 | 0.987 | 0.983 | 0.985 | 0.99 | | | | | |
| HC $M_{30}$ | $2E-07x^2 - 0.0002x + 1.0011$ | 1 | 0.965 | 0.94 | 0.935 | 0.93 | | | | | |
| CC $M_{30}$ | $2E-07x^2 - 0.0001x + 0.9997$ | 1 | 0.975 | 0.967 | 0.965 | 0.96 | | | | | |
| HC $M_{40}$ | $3E-07x^2 - 0.0004x + 0.9993$ | 1 | 0.935 | 0.895 | 0.885 | 0.89 | | | | | |
| CC $M_{40}$ | $2E-07x^2 - 0.0003x + 0.998$ | 1 | 0.95 | 0.925 | 0.915 | 0.91 | | | | | |

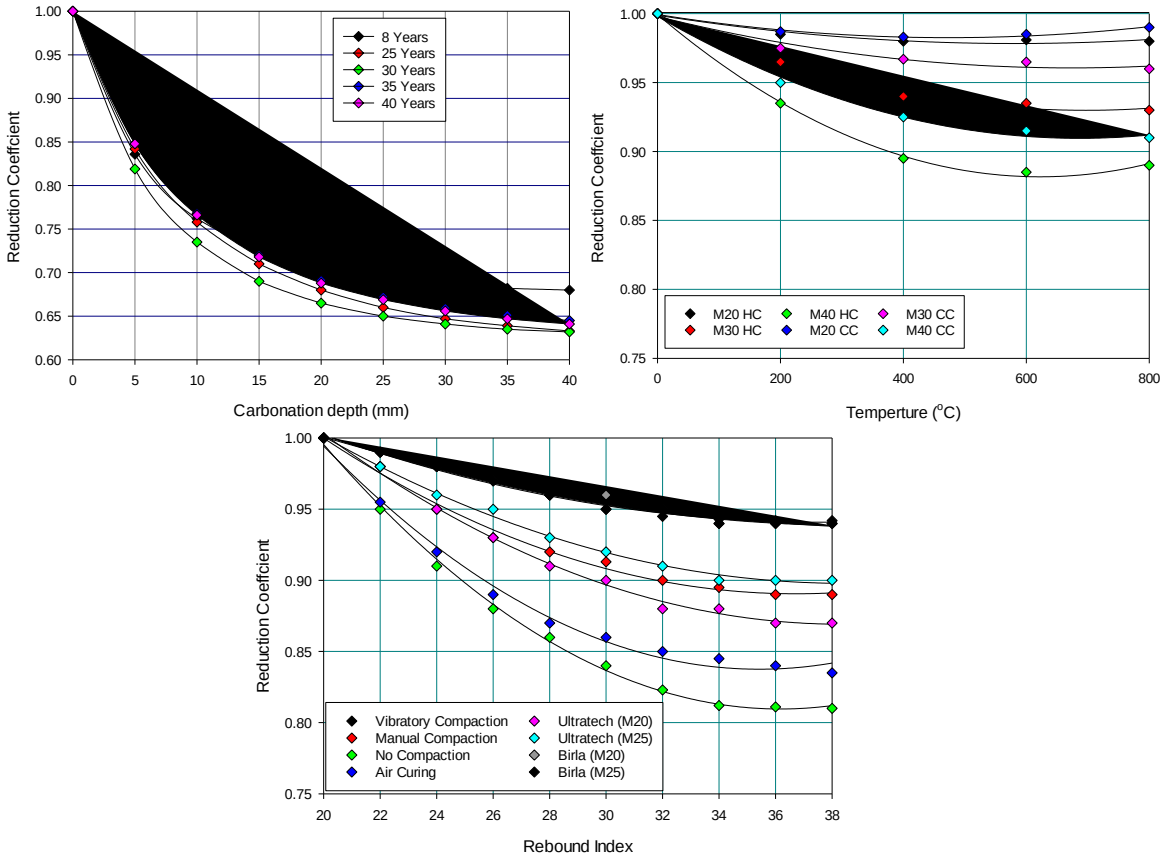



Fig. 3.17 Reduction coefficient curve a) Effect of Carbonation depth, b) Effect of influencing parameters. c) Effect of elevated temperature

# CHAPTER 4

## SUMMARY AND CONCLUSIONS

1. The average rebound index and compressive strength of concrete are time-dependent material properties. A single function cannot directly correlate to it. Hence, the relationship needs multiple roles, where independent variables are types of cement, curing conditions, compaction methods, temperature variation, and water-to-cement ratio.
2. Researchers derive the Regression equations from the results of laboratory tests that can only be used within their implementation limits. Hence estimating strength by Schmidt rebound hammer may be higher than expected.
3. The coefficient of variation decreases with an increase in mean compressive strength, but no such variation is observed in the case of the mean rebound index. It indicates the effect of influencing factors on the coefficient of variation.
4. The present study provided efficient mathematical, linear and non-linear relationships that would enable engineers to estimate the strength of the concrete with minimum error.
5. The regression coefficient of only 65 % was achieved when different types of cement were used in making specimens. It indicates that the cement type change is not reflected in the rebound index. The regression coefficient of curves is also very low in the case of factors like curing and compaction methods.
6. Variable compactions significantly affect the rebound index, and the same scenario is seen in the case of curing methods. For the same values of rebound numbers, the compressive strength of concrete with different curing methods is reduced by 25–50 % than concrete cured under normal conditions.
7. The change in the rebound index due to a change in the water-cement ratio at the same age significantly increased the rebound value.
8. Temperature variations have considerably affected the rebound index and concrete's compressive strength. As the temperature rises, the surface hardness of the specimens increases, resulting in an ambiguous rebound index.
9. In the case of higher grade concrete, i.e. M30 and M40, the compressive strength is greatly affected at high temperatures than in the case of M20 grade concrete.
10. The percentage of mass loss is higher up to 400◦C. From 400 to 800◦C, the temperature quickly decreases the compressive strength, which may fail structure.
11. Air cooling specimen’s shows higher compressive strength compared to hot condition. The surface hardness for the hot state specimen is high compared to the normal cooling state.
12. The rebound index was higher at elevated temperatures than at normal air cooling temperatures due to a more rigid surface under elevated temperatures.
13. Considerable deviation in rebound index vs compressive strength curves indicates the influence of various factors. It raises a crucial question on whether the use of a rebound hammer is effective or not in estimating concrete strength without considering these factors.
14. There is an urgent need to develop/modify the NDT test standards, considering the factors affecting the rebound index.

15. The effect of the types of cement used to prepare concrete mix can be observed prominently. CT-I shows poor performance, particularly in the lower grades of concrete compared to that of CT-II.
16. The compressive strength is reduced by 6 − 41% due to compaction deficiency alone. The reduction of the rebound index reported by Schmidt's rebound hammer is almost half of the compressive strength in the case of the specimens compacted manually.
17. The variation in the average compressive strength of samples cured under only air and water is noticeable. However, the average rebound indices reported by Schmidt's hammer are almost the same, regardless of the age of the concrete. Hence, it is concluded that the rebound hardness test cannot predict compressive strength affected by inadequate curing.
18. The rebound hammer does not give true values for cube specimens prepared with different w/c ratios. Nevertheless, a decrease in the w/c ratio has enhanced the average rebound index and concrete compressive strength when tested at the same age.
19. The percentage reduction of the average rebound index of the M30 and M40 grade mixtures is almost higher in all the cases than the average compressive strength at temperatures ranging from 200°C to 800°C. The percentage variation in compressive strength loss for M30 mix and M40 mix grade at temperatures, i.e., 400°C to 800°C, is higher than that of M20 mix concrete specimens.
20. Due to the scale design of the rebound hammer, measurement error may be reached up to 20%. It is proposed that there should be a change in the scale of the index rider, which shows only the even values arising from the error of observations. Thus, removing this type of error will involve an index rider scale that will show both even and odd values rather than only even values.
21. The specific curve of EN 13791 for the hardness test is not arbitrarily set to the minimum level, at which a positive change can always be made for the true strength assessment.
22. According to ACI 228.1R-03, the repeatability parameters of the rebound effects are closer to those of the concrete strength variations. It recognizes that no consistent trend is observed, and the increasing average shows a decreasing trend.
23. The standard deviation of the probability distribution of the rebound outcomes and their ranges matches the lognormal distribution with a strong positive skewness.
24. Experimental results cannot match the ASTM C 805 outcomes; it is suggested that the statements in ASTM C 805 regarding the SD and rebound range values be reconsidered.
25. The COV of the rebound index is significantly affected by cement types, concrete grades, degree of compaction, curing condition, elevated temperature, and concrete w/c ratios. It should consider these factors for accurate strength estimation.
26. The normalized range of rebound index and compressive strength indicates that 97% of results are less than 9%. Hence, as per EN 12390-3, the results obtained in the present study are reliable and can be considered even if the specimens are prepared from locally available materials.

# CHAPTER 5

# FUTURE WORK

- There is an urgent need to provide separate calibration curves or correction factors according to various influencing factors in the present BIS code.
- Conducting a detailed investigation on carbonation and modulus of elasticity effect on rebound hardness is essential.
- There is a need to use advanced equipment with Nondestructive testing devices for accurate and precise results.
- Calibrations of current devices using proposed curves based on engineers' and consultants' needs.
- Modifications/periodical changes are essential in empirical curves according to material and present environmental conditions.

# PUBLICATION

**ARTICLES PUBLISHED IN JOURNAL** (SCI, SCOPUS, WOS)

1. Factors influencing the performance of rebound hammer used for non-destructive testing of concrete members: A review, Case Studies in Construction Materials, vol. 14, 2021, e00491, ISSN 2214-5095, https://doi.org/10.1016/j.cscm.2021.e00491 (IF- 3.328)
2. Repeatability of concrete rebound hardness using comprehensive statistical analysis, Journal of King Saud University - Engineering Sciences, 2021, https://doi.org/10.1016/j.jksues.2021.02.013 (IF- 4.806)
3. Experimental Investigations on Effect of Compaction, Curing, Water to Cement Ratio, Cement Type and Temperature Variation on the Rebound Hardness of Concrete. KSCE J Civ Eng 25, 1857–1864 (2021). https://doi.org/10.1007/s12205-021-1508-5 (IF- 1.805)

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1. Experimental investigation on relationships between rebound index and compressive strength of cement concrete specimen influenced by physical factors, Advances in Science and Engineering Technology International Conferences (ASET), Dubai, United Arab Emirates, 2020, pp. 1-5, DOI:10.1109/ASET48392.2020.9118246.
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3. SonReb Method for Evaluation of Compressive Strength of Concrete. IOP Conference Series: Materials Science and Engineering. 810. 012071. DOI:10.1088/1757-899X/810/1/012071.

**IPR GRANTED**

Design patent (**Concrete Scanning equipment**332140-001,

**RESEARCH GRANT RECEIVED**

Title of project: Condition assessment of concrete quality by Non Destructive testing.
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